Pricing Defaulted Bonds - Evidence from Markets, CDS Auctions and Ultimate Recovery.

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As members of the Dissertation Committee, we certify that we have read the dissertation prepared by **Sunil Kumar Teluja**, titled **Pricing Defaulted Bonds – Evidence from Markets, CDS Auctions and Ultimate Recovery** and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

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Abstract

I examine pricing of bonds at Credit Event Auctions which are used to calculate settlement payouts on Credit Default Swaps underwritten on issuing firms that have triggered a credit event. Secondary market prices of bonds along with those discovered at the auction are estimates of terminal recovery on these securities which is conventionally referred to as ultimate recovery. I use hand-collected data on ultimate recovery on these bonds to jointly test for bias in prices at the auction and in secondary markets. I find that Credit Event Auctions are biased in a manner consistent with theory and generate prices that, on average, underestimate ultimate recovery resulting in higher payouts to buyers of credit protection. Moreover, bond prices in secondary markets are more informed about ultimate recovery before the auction than after it suggesting that existence of open CDS positions enriches the information environment for these bonds.

1 Introduction

A single name credit default swap (CDS) is a contract between two parties in which one (protection-seller) agrees to indemnify the other (protection-buyer) against the occurrence of a credit event pertaining to a specific entity (sovereign or corporate) which has credit instruments (bonds and/or loans) due and outstanding. By convention, contracts underwritten on bonds are referred to as CDS while those underwritten on loans are called Loan CDS or LCDS. The contract can be designed to cover a wide range of credit events such as failure to pay, default, and various forms of restructuring.

The amount of indemnity to be paid is not explicitly defined (in most cases) but is a function of the notional value of the contract which corresponds in character and purpose to the par value of the underlying entity's credit securities. Settlement of the CDS contract on occurrence of a credit event thus results in a transfer between the protection seller and the protection buyer so as to compensate the buyer for the credit event[1]. Since this amount (loss incurred and/or indemnified) is unspecified when the CDS is contracted, settlement of a single name CDS requires a mechanism to determine both the amount and composition of the transfer between parties to the contract.

CDS are widely used by hedgers and speculators to exchange credit risk in the economy, and, for many individual firms, the CDS market is larger and more liquid than the market for their bonds and/or loans (Oehmke and Zawadowski (2016)). Since the purpose of a CDS contract is to transfer credit risk, a critical component of this market is the mechanism used for settlement of CDS contracts on occurrence of a credit event.

Since 2006, single name CDS (and LCDS) contracts are settled (on occurrence of a credit event) in a two stage auction conducted by Creditex and Markit. The auction seeks to price bonds underlying the CDS contract in order to calculate

[1]The protection-buyer does not necessarily have a position in the bonds of the underlying entity.

the payout to CDS buyers (buyers of credit protection). The price of these underlying bonds in the auction is an estimate of recovery[2] and the difference between par value and auction price is determined as the notional loss to CDS buyers. CDS buyers are compensated for this notional loss by CDS sellers (sellers of credit protection) in full settlement of open CDS contracts. The structure of the auction allows for both cash[3] and physical[4] settlement.

The auction is conducted concurrently with the trading of bonds in secondary markets. Secondary market prices therefore represent another estimate of recovery. By convention, final recovery from impaired securities is referred to as ultimate recovery. Testing for bias in bond prices from secondary markets and credit event auctions is econometrically tedious. This is because both the auction price and market price of bonds are estimates of ultimate recovery and bias in one can not be inferred by benchmarking it to the other. I ameliorate this issue by using hand-collected data on ultimate recovery from bankruptcy documents and SEC filings. Since ultimate recovery refers to the amount recovered by holders of a credit security on resolution of a credit event, it represents the most appropriate benchmark for recovery estimates yielded by the auction and secondary market prices. I seek to examine the pricing of bonds in default by jointly comparing estimates of recovery from Credit Event Auctions and secondary market prices against ultimate recovery.

First, I investigate Credit Event Auctions for bias by comparing recovery estimates from auctions to ultimate recoveries on underlying securities. I show that, on average, recoveries (prices) in CDS auctions are downward biased estimates of

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[2]Recovery refers to the amount that is recovered from the impaired security in full settlement of claims. Recovery is usually expressed as a percentage of the par amount outstanding and called the recovery rate.

[3]Cash settlement implies that the CDS seller (seller of credit protection) compensates the CDS buyer (buyer of credit protection) by making a cash payment for the loss on the underlying securities. In percentage terms, this loss is one minus the recovery rate discovered in the two stage auction.

[4]Physical settlement implies that the CDS buyer delivers impaired bonds of the underlying firm to the CDS seller in return for their par value in cash.

ultimate recovery. For individual auctions, the direction of bias is correlated to first-stage auction outcomes in a manner consistent with theoretical predictions of Chernov, Gorbenko, and Makarov (2013) but not of Du and Zhu (2017). This implies that when the CDS position of protection buyers (CDS buyers) is larger than their bond position, auctions are likely to under-price recovery (leading to higher pay-off for CDS buyers and greater loss for CDS sellers). These results indicate that the settlement of CDS contracts is inefficient and biased.

Next, I examine the informativeness of bond prices in secondary markets around the auction. Specifically, I benchmark bond prices (which are market estimates of ultimate recovery) to ultimate recovery and test for bias in several time windows before and after the auction. I find that bond prices are more informed about ultimate recovery prior to the CDS auction but become noisier estimates of recovery thereafter. This suggests that the existence of open CDS positions (before the auction) enriches the information environment for bonds in default and reduces bias in their pricing[5].

Lastly, due to differential classification during the bankruptcy process, all issues underlying an auction do not yield the same ultimate recovery. I exploit this heterogeneity in ultimate recoveries among various issues of the same firm for additional tests of bias in the auction and secondary market prices. I find that auction prices are biased (albeit with reduced significance) even when they are benchmarked against the issue with the lowest ultimate recovery among all issues underlying an auction. This allows me to account for the cheapest to deliver option in my analysis of bias in the auction. The cheapest to deliver option states that, when several securities are eligible for delivery at an auction, only the issue with the lowest ultimate recovery will be delivered under the assumption that auction participants are sufficiently informed about ultimate recoveries on all underlying issues. Therefore, under the condition that the cheapest to deliver phenomenon is in force at the auction, auction prices should be benchmarked

[5]Appendix B contains a detailed discussion on bond prices and ultimate recovery.

to the issue with the lowest ultimate recovery as that is the issue which is most likely to have been transacted at the auction.

Data on ultimate recoveries for various issues of the same firm also allows me to test if secondary market prices are informed about heterogeneity in ultimate recovery among these issues. In line with earlier results, I find that secondary markets seem to be more informed about the variation in ultimate recovery within issues of the same firm before the auction than after it.

Single name CDS constitute one of the largest derivative markets in fixed income with an outstanding gross notional value of USD 4.7 trillion and a net notional value of USD 542 billion as at November 2017[6]. Single name credit default swaps are also employed in the construction of several CDS indices and the settlement of these indices is benchmarked to auction outcomes of single name contracts[7]. These indices have an outstanding gross notional of USD 6 trillion and a net notional value of USD 900 billion. Besides being large markets in themselves, these instruments are widely used by hedgers and speculators to trade credit risk due to higher liquidity and standardized contracts. Bias in the settlement of single name CDS can therefore lead to economy-wide mispricing of credit risk.

Moreover, since CDS spreads are widely used in financial research and decision making, mispricing of recovery risk (due to settlement being biased) inherent in these contracts can have wide-ranging practical implications. Additionally, the arbitrage relationship between bond spreads and CDS is based on the equivalence between loss on bonds and the pay-off from CDS on settlement, and would fail if the settlement of CDS is inefficient. This question also has implications for the CDS-Bond basis which is used widely as a proxy for liquidity and limits to arbitrage[8]. Lastly, these results have regulatory implications for CDS as the bias

[6]According to Bank for International Settlements, gross-notional refers to the sum of the par value of all CDS trades. Net-notional refers to the sum of the par values of all open CDS contracts.

[7]See Markit Credit Indices- A Primer, November 2008.

[8]Nashikkar and Subrahmanyam (2007), Nashikkar, Subrahmanyam, and Mahanti (2011),

in settlement seems to consistently benefit a certain type of participant in CDS markets (net buyers of CDS).

While much research exists on other aspects of CDS markets[9], a joint investigation of recovery estimates yielded by the auction and bond markets (crucial to well functioning fixed income markets) is missing from the literature. Prior studies examining this question benchmark auction recovery to bond prices and provide descriptive evidence supporting mixed results. Helwege, Maurer, Sarkar, and Wang (2009) estimate the absolute difference between auction recoveries and bond prices just prior to the auction and find these differences to be small. They infer from the minuteness of these differences that CDS auctions are unbiased. By contrast, Gupta and Sundaram (2012) identify a V-shape pattern in prices of bonds eligible for delivery in certain auctions around the auction date. They infer auction bias from these price patterns. Chernov, Gorbenko, and Makarov (2013) use these V-shape patterns to support their theoretical predictions of underpricing in certain types of auctions. Du and Zhu (2017) predict biased outcomes from the auction in comparison to a theoretical double auction which they find to be efficient.

Previous studies have also been constrained by the availability of bond prices in examining the effect of cheapest to deliver issues on auction outcomes. Specifically, Chernov, Gorbenko, and Makarov (2013) use prices of bonds trading cheapest prior to auction as the cheapest to deliver benchmark for auction prices. However, bonds trading cheapest prior to auction may not be the cheapest to deliver in economic terms if the true cheapest to deliver issue is not traded, thinly traded or mispriced by the market. Since I identify cheapest to deliver issues on the basis of ultimate recovery, my analysis is free of estimation biases on account of market frictions.

Bai and Collin-Dufresne (2011).

[9]An indicative list is Oehmke and Zawadowski (2016), Acharya and Johnson (2007), Arora, Gandhi, and Longstaff (2012), Bolton and Oehmke (2011), Duffie (1999), Garleanu and Pedersen (2011), Longstaff, Mithal, and Neis (2005), Pan and Singleton (2008), Parlour and Winton (2013), Blanco, Brennan, and Marsh (2005), Bai and Collin-Dufresne (2011).

My study is also related to literature examining the ability of secondary market prices of bonds in default to impute recovery. Specifically, Warner (1977), Eberhart and Sweeney (1992) and Altman and Eberhart (1994) examine this question and arrive at equivocal conclusions about the informativeness of bond prices vis-a-vis recovery. I examine this question in the context of CDS auctions which is new to the literature.

Moreover, Oehmke and Zawadowski (2016) also investigate linkages between CDS and bond markets and conclude that the CDS-Bond basis trade improves liquidity and informativeness of bond prices. While Oehmke and Zawadowski (2016) focus on these linkages prior to default, I test for these linkages post the occurrence of a credit event. Another stream of literature, most notably Jiang, Li, and Wang (2012) and Wang (2011) look at the impact of factors such as the presence of hedge funds and bankruptcy and liquidation costs on bankruptcy outcomes and returns of various classes of bonds in default. My findings complement these studies by identifying and documenting the information contribution of open CDS positions to the pricing of bonds in default.

The remaining study is organised in to several sections. Section two describes the CDS auction with an example. Section three discusses the advantages of ultimate recovery in auction prices, section four documents the data collection process, section five discusses main findings and section six concludes.

2 The CDS Auction

The current auction format for CDS settlement was designed in response to issues arising out of physical-settlement of Delphi CDS contracts. With notional value of CDS contracts many times larger than bond-notional, many CDS contracts on Delphi had to be modified to provide for cash settlement. The current two stage auction format was first used for settling contracts on Dura in 2006 and has become standard since.

A CDS settlement is triggered by the occurrence of a credit event as determined by a Determination Committee[10]. Once a credit event has been determined, a list of securities issued by the reference entity is voted upon by members to be made eligible for delivery in the CDS auction[11].

The auction is divided into two stages with outcomes of the first stage used in the second stage. Only CDS holders (agents with open CDS positions) are allowed to participate in the first stage of the auction while the second stage is open to non CDS holders as well. In the first stage, dealers submit quotes for the prices at which they are willing to both buy and sell eligible securities. They also have to specify the quantity of these bonds/loans (par value) that they wish to either submit or accept in physical settlement of their CDS contracts. These quantities are called Physical Settlement Requests (PSR). Dealers are constrained from submitting PSRs that are in a direction opposite to their CDS positions. This means that if a dealer is a buyer of credit-protection, she can only submit a PSR of sell, for a quantity less than equal to her long position in CDS and vice versa.

At culmination of the first stage of bidding, bids and offers from two way quotes that cross are eliminated and an average of the best halves of the remaining quotes becomes the Initial Market Midpoint or IMM. Dealers with off market quotes are penalized by an amount called the adjustment amount. The PSRs are aggregated across all dealers and Net Open Interest (NOI) is determined. If SELL PSRs exceed BUY PSRs then the NOI is SELL. Likewise, if BUY PSRs

[10]There are five Determination Committees, one for each region of the world.They were set up as part of the changes brought about by ISDA to streamline trading and settlement of credit derivatives. Each Determination Committee is a regional committee composed of 15 members, 10 of whom are dealers. Membership is reassessed annually. The occurrence of a credit event is decided upon by the Determinations Committee through voting and requires a super majority of 80 percent, failing which, it is referred for external determination.

[11]The list may not encompass all outstanding securities (even if they are senior) and in many cases securities of same seniority or those subjected to lock ups in a bankruptcy are excluded. After eligible securities, quotation amounts, and maximum bid-ask spreads have been specified by the Determinations Committee, the auction date is determined and published.

exceed SELL PSRs then NOI is BUY[12]. The first stage concludes with declaration of the size and direction of the NOI, the IMM and the adjustment amounts.

The second stage requires participants to submit limit orders to fulfill the NOI. This means that if the NOI is SELL, participants submit limit bid orders to buy the bonds and vice versa. Dealer quotes from the first stage are automatically carried forward as limit orders to buy at the bid and sell at the offer depending on the direction of the NOI. A price cap/floor is also imposed. Usually the cap/floor amount is set at one percent of par value. For SELL NOI, limit orders to buy cannot be submitted at a price greater than the IMM plus the cap amount. Similarly for BUY NOI, limit orders to sell cannot be at a price less than the IMM minus the floor amount. Thus for a SELL NOI there is a price cap of IMM plus the cap amount and for a BUY NOI there is price floor of IMM minus the floor amount amount. The second stage concludes with matching of the NOI to limit orders and the price at which the NOI is fulfilled is the final auction price at which all contracts are settled[13]. This settlement price represents the recovery rate for cash settlement of CDS contracts and the NOI allows for physical settlement.

For example, suppose a buyer of credit-protection has a CDS position of USD 100 million in notional terms and holds deliverable bonds with a par value of USD 50 million. Under a physical settlement regime she will have to purchase bonds with a par value of USD 50 million and tender all her bonds (now aggregating to USD 100 million in par) in return for USD 100 million in cash from her counterparty. If the price of these bonds in the secondary markets is 50 percent of par, her outflow will be USD 25 million (to purchase additional bonds) and her net inflow will be USD 75 million. Assuming that bond supply is unlimited at a price of 50 percent of par and that this price is an unbiased expectation of the recovery

[12] SELL PSR means that the dealer wants to physically settle her position as a buyer of credit protection by delivering eligible bonds in return for par.

[13] This means that bonds that were a part of the unfulfilled PSRs from first stage are bought or sold at the final price. CDS positions which were still open after matching of PSRs in first stage are settled in cash at the auction price. This means that protection sellers pay protect buyers par minus auction price to cash settle their contracts.

on bonds, the CDS auction will also yield the same payoff.

If settlement is implemented through the current auction format, the buyer of credit-protection can submit a SELL PSR of USD 50 million in the first stage[14]. Assuming that she is the only participant with a SELL PSR and that her PSR is fulfilled only to the extent of USD 25 million, the NOI will be USD 25 million to SELL at the end of the first stage. This means that bonds amounting to the NOI will be auctioned in the second stage. If the auction is efficient, it will yield a settlement-price equal to the true recovery value of 50 percent of par and she will be able to sell the USD 50 million (par value) of her bonds for USD 25 million. Since she had a CDS position of USD 100 million, it will be cash settled at 50 percent of par (settlement-price) leading to a cash inflow of USD 50 million. Her total settlement inflow in return for all her bonds will be USD 75 million in cash. This matches her inflows under a physical-settlement regime.

Thus under the auction, CDS counter-parties have two sources of flows: physical-settlement of bonds transacted at the settlement-price and cash-settlement of CDS positions at the settlement-price.

3 Benchmarking Auction Recovery

Prior studies have relied on bond prices as estimates of recovery to examine CDS auctions. However the auction is contemporaneous to trading of bonds in secondary markets and thus bond and auction prices are jointly determined. Ultimate recovery is the outcome of a legal process and independent of bond trading in secondary markets thereby making it a better candidate for benchmarking auction recovery. Helwege, Maurer, Sarkar, and Wang (2009) analyze the absolute difference between the auction recoveries and bond prices prior to the auction and infer from the small variance in these prices that the auction is efficient. They assume bond prices to be a suitable benchmark for the purposes

[14] As a buyer of credit-protection, she can submit a SELL PSR to the extent of her CDS position of USD 100 million.

of examining the efficiency of auction recoveries.

Under the same assumption, Gupta and Sundaram (2012) describe and map a V-shape pattern in the prices of bonds eligible for delivery in SELL NOI auctions around the auction date. They interpret these patterns as descriptive evidence in support of auction inefficiency.

Chernov, Gorbenko, and Makarov (2013) theorize that auction participants with CDS positions larger than their bond positions have incentives to act strategically during the auction which can lead to underpricing equilibria where the auction recovery is lower than true recovery. In their model, actions by such participants can not be nullified by their counter-parties since they are constrained from holding/purchasing bonds that are in default. Chernov, Gorbenko, and Makarov (2013) therefore surmise that SELL NOI auctions should lead to underpricing of recovery. They assume bond prices prior to the auction to be a suitable benchmark for auction prices. They interpret the V-shape pattern in bond prices (Gupta and Sundaram (2012)) as evidence, in support of their theory.

Du and Zhu (2017) theorize that participation constraints make CDS auctions inefficient. Contrary to Chernov, Gorbenko, and Makarov (2013) they predict underpricing of recovery for BUY NOI auctions and overpricing of recovery for SELL NOI auctions. In their model, the participation constraints imposed in the first stage of the auction and the one way market in the second stage of the auction hinder optimal allocation and efficient price discovery. Their theoretical benchmark for auction recovery is the outcome from a double-auction which they consider to be efficient[15]. The possibility that bond and auction prices could be determined by a joint equilibria has not yet been addressed theoretically. Also both Chernov, Gorbenko, and Makarov (2013) and Du and Zhu (2017) assume that the supply of deliverable bonds is unconstrained, which is unlikely.

Thus there is considerable divergence in the literature on the existence and direction of bias in CDS auctions. Theoretically, Chernov, Gorbenko, and Makarov

[15] Appendix C contains a detailed discussion of the theory underlying CDS auctions.

(2013) and Du and Zhu (2017) provide contradictory predictions. This is further complicated by the fact that these studies use different benchmarks for auction recoveries in arriving at their predictions. Descriptive evidence provided by Helwege, Maurer, Sarkar, and Wang (2009) supports auction efficiency while Gupta and Sundaram (2012) and Chernov, Gorbenko, and Makarov (2013) infer bias from price patterns around the auction.

In order to verify if recovery estimates based on bond prices yield consistent and unequivocal evidence on the efficiency of CDS auctions, I replicate the main results of Helwege, Maurer, Sarkar, and Wang (2009) and Gupta and Sundaram (2012). In line with Helwege, Maurer, Sarkar, and Wang (2009), I compare bond prices on the day of auction to auction recovery rates using a scatter plot. Figures 1, 2 and 3 represent these plots for all auctions, SELL NOI auctions and BUY NOI auctions respectively. A majority of the observations for all three sets of data lie on the 45 degree line, indicating that for most auctions bond prices on the day of the auction do not deviate significantly from auction recovery. This implies that based on bond prices on the day of the auction, auction outcomes seem unbiased and efficient.

I also replicate the descriptive analysis of Gupta and Sundaram (2012). I express bond prices as a percentage of the auction recovery and plot them over a time window spanning the auction date. While Gupta and Sundaram (2012) and Chernov, Gorbenko, and Makarov (2013) plot these prices over a window spanning 5 days before and after the auction, I plot bond prices over windows spanning 10 and 15 days as well. Figures 4, 5 and 6 show the evolution of bond prices over these time windows. Bond prices exhibit a shallow V-shape pattern in the 5 days preceding and following the auction but do not exhibit a distinct V-shape pattern when the time window is expanded to 10 and 15 days. This implies that, assuming bond prices are efficient before and after the auction, the auction is biased based on the bond prices only in the 5 day window. This inference however, does not hold when the window is expanded to 10 and 15 days preceding and following the auction.

In sum, replication of previous studies yields contradictory results. Bond prices on the day of the auction do not support auction bias. Under the assumption that bond prices before and after the auction are efficient, auction bias is supported by bond prices in the 5 days preceding and following the auction but not by bond prices in the 10 and 15 day windows. Moreover, the assumption that bond prices preceding and following the auction are fully informed is potentially problematic[16]. Conversely, it can be argued that since the auction day is likely to witness maximum participation in the markets by both bond and CDS holders, bond prices on auction day (which are very similar to auction prices) are more informative than prices before and after the auction. Under this assumption, the V-shape pattern in bond prices could be seen as an affirmation of auction efficiency.

Therefore, recovery estimates based on bond prices yield ambivalent results about bias in CDS settlement and questions regarding the existence and direction of bias in CDS auctions remain unresolved. I address this question jointly with the question of informativeness of secondary market prices using ultimate recovery[17].

4 Data

4.1 The Recovery Data

I hand collect data on ultimate recovery from several sources described in detail later in this section. My sample contains all observations pertaining to CDS auctions on US and Canadian entities that underwent bankruptcy/liquidation or restructuring from 2006 to 2016.

One advantage of using this data is that ultimate recoveries can be calculated for every security eligible for delivery at the CUSIP level. There is a considerable

[16]See Appendix B.

[17]Appendix A contains a detailed discussion on various measures of recovery.

amount of heterogeneity in the ultimate recoveries of securities that are deliverable for the same auction. Given the fact that the auction yields a single estimate of recovery, I use both an average of the recoveries across issues and the lowest of all recoveries across issues (to account for the cheapest to deliver option) for my analysis.

I also include LCDS auctions which have hitherto remained unexplored and where the usage of secondary market data would be problematic on account of poor frequency of trading and price data. Thus I have a relatively large sample of 70 observations compared to 25 (at maximum) for all previous studies.

Data for ultimate recoveries comes from two main sources: bankruptcy documents and SEC filings. Among the bankruptcy documents, two most critical ones are the final plan of reorganization and the accompanying disclosure statement. The plan of reorganization provides a qualitative framework of the restructuring envisaged and outlines the seniority of the claims. More importantly the disclosure statement provides quantitative information about the pre-petition capital structure, value of claims, mode of claim settlement and estimated recoveries on various classes of claims. It also contains details of assumptions underlying recovery estimates which include the number and estimated value of distributions to be made pursuant to emergence from bankruptcy and estimated distributable value of the assets. Sometimes these documents are inadequate to ascertain actual quantity and value of distributions made and I refer to SEC documents filed upon emergence to acquire this information. In some selected cases I also refer to documents from liquidating trusts (for Lehman Brothers) to arrive at the nominal value of distributions.

A vast majority of recoveries are in the form of equity in the reorganized firm. While an estimate of reorganized equity value is provided in the disclosure statement I do not use it because it can be significantly different from actual equity value. Therefore I average daily prices for a month post-listing upon emergence from bankruptcy to estimate equity value which is then used to compute recoveries. Stock price data are from CRSP. In some cases where shares are not listed on an exchange I use OTC market data but only include price observations which are accompanied by trading volume. Some recoveries are in the form of re-priced/new debt/loans or reinstatements. I take these at face value. While one-time cash distributions require no adjustments, in case of liquidations where a series of cash distributions occur over a period of time I aggregate all the distributions and assume that they occur on the last distribution date.

Some observations have been excluded on account of lack of data and/or clarity vis a vis the implications of the credit event on ultimate recovery. These largely pertain to restructurings or strategic bankruptcies. While I include most US/Canadian bankruptcies from 2006 to 2016, I exclude 5 observations. Dex One and Supermedia bankruptcies are excluded because these bankruptcies were strategic. The two firms intended to merge for which a modification to their existing credit agreements was required. Upon being refused the said modification by creditors, they simultaneously entered bankruptcy to facilitate the change in the credit agreement and consummate the merger. The effect on ultimate recoveries and/or impairment is unclear in this case and hence these observations have been excluded. The Cemex credit event was triggered by a restructuring that modified the repayment schedule of liabilities. Again in this case the impact on ultimate recoveries and/or impairment suffered by the creditors is unclear and hence this observation has been excluded. Sinoforest and Radioshack went into liquidation and no information is available on ultimate recoveries. The case of Lehman Brothers is somewhat special in my sample. I could not acquire information on securities eligible for delivery in the Lehman CDS auction (ISDA web links are broken, ISDA did not respond to my requests for the data). Therefore for Lehman, I use distributions made to senior unsecured bond holders of LBH Inc to estimate ultimate recoveries for the CDS auction. In my assessment since a majority of the senior unsecured debt in the Lehman bankruptcy was on account of the above mentioned securities, my estimates should be fairly representative of the ultimate recoveries on actual securities eligible for delivery.

Lastly because there is substantial heterogeneity in the ultimate recoveries of deliverable securities for the same auction, I aggregate them to a single ultimate recovery estimate by taking an average of the ultimate recoveries weighted by value of the claim outstanding on default. In order to account for the cheapest to deliver option, I perform all empirical tests with only the lowest ultimate recoveries as well.

4.2 Adjusting Ultimate Recoveries

The ultimate recovery rate based on the cash flows or distributions on resolution of bankruptcy is nominal in nature because it has not been adjusted for the passage of time and changes in state variables that impact recovery. This rate is not directly comparable to recovery from CDS auctions that take place within 30 days of the credit event. According to Altman, Resti, and Sironi (2004) there are two approaches to adjust nominal ultimate recoveries so as to make them comparable to recoveries estimated near the time of default. One way is to convert nominal recoveries to certainty equivalents and discount them by the risk free rate. The other is to discount them with a rate that represents the risk free rate and a premium for the recovery rate risk. I employ both approaches to adjust nominal ultimate recoveries. For the second approach, I find a suitable proxy for recovery rate risk and the premium associated with it.

Acharya, Bharath, and Srinivasan (2007) estimate ultimate recovery from secondary market prices of bonds upon emergence from bankruptcy. They show that the cumulative returns on a high yield index can be used for deflating nominal ultimate recovery so as to make it comparable to estimates of recovery just after default. Accordingly I use the Bloomberg Barclays North America High yield index as one of the proxies for adjusting nominal ultimate recoveries.

I also use the Altman-Kuehne defaulted bond index and the Altman-Kuehne defaulted loan index for adjusting CDS and LCDS ultimate recoveries respectively. These indices comprise of bonds and loans that are in default and track their price performance. They are value weighted by the par-amount issued of each of the instruments that comprise it. These indices are suitable for this study since they represent the average return for the exposure to state variables that impact recoveries, for a cross section of bonds and loans that are in default. They also have the added advantage of allowing me to use a distinct Defaulted-Loan index to deflate ultimate recoveries for LCDS auctions. This is important because loans deliverable for LCDS auctions are senior-secured and the factors impacting their ultimate recovery are likely to be different from those for unsecured bonds.

Moody's Ultimate Recovery Database uses coupon rates on issuance to adjust the nominal ultimate recoveries. Given the fact that there is no reason to assume that the coupon at issuance is a good proxy for the factors that drive ultimate recovery post-default, I avoid this approach in favor of using the Altman-Kuehne indices and the Barclays High Yield index.

4.3 Bond Data

A part of my analysis also requires data on bond prices. I use the Enhanced TRACE database. Bond price data is at the transaction level which necessitates the application of certain assumptions in determining the most representative price. The data also has duplication and redundancy which has to be corrected in order to ensure its informativeness.

TRACE data has well documented issues on account of duplication, cancellation of trades, reversal and amendment of trades and agency transactions. I broadly follow Dick-Nielsen (2009) and Dick-Nielsen (2014) to ameliorate these issues. I eliminate all duplicate trades by sorting on price, volume, transaction date, transaction time and message sequence number. Next, I cull all trades and same day cancellation reports assigned to them from the database by using the original message sequence number variable. Lastly, I match cancelled trades with executed trades on all parameters to eliminate reversals. Agency transactions are allowed to remain in the sample.

I follow Bessembinder, Kahle, Maxwell, and Xu (2008) and compute volume weighted prices for each issue for each day in my sample. These prices are averaged over all eligible issues for varying time intervals depending on the test-design.

5 Results

5.1 Summary Statistics and Univariate Results

My sample consists of 70 observations (out of which one has zero NOI after the first stage of the auction) which are divided on the basis of the type of derivative instrument for which the auction was held (CDS or LCDS) and NOI (Net Open Interest) at the end of the first stage of the auction (BUY or SELL). For each subsample I focus on the following variables: NOI amount; NOI amount adjusted by the claim outstanding for deliverable securities at the time of the credit event; Nominal or unadjusted ultimate recovery on deliverable securities (Nominal Ultimate Recoveries); ultimate recovery that has been adjusted using Altman-Kuehne defaulted bond or defaulted loan index as the case may be (Altman Adjusted Ultimate Recovery); and ultimate recovery that has been adjusted using the Bloomberg Barclays North America High Yield Index (High Yield Adjusted Ultimate Recovery). I also compute the time (in days) from the auction to ultimate recovery and the number of issues eligible for delivery at the auction. For each of the above variables, in each of the above sub-samples, I compute mean, median, minimum, maximum and the standard deviation. This information is contained in Tables 1 to 4.

Table 1 provides descriptive information on the entire sample. Mean and median recoveries in the auction are 36.7% and 23.9% respectively which is much lower than the mean and median nominal ultimate recoveries of 63.4% and 66.7%. Mean and median differences between the nominal ultimate recovery and auction recoveries are 26.6% and 22.7% respectively. On an adjusted basis the mean and median differences compress significantly to 9% and 6.1%, when adjusting with the Altman-Kuehne index, and 10.6% and 7.1%, when adjusting with the Bloomberg Barclays Index. Thus preliminary descriptive statistics suggest that, on average, ultimate recoveries are higher than auction recoveries.

Table 2 contains summary information on the sample of auctions with non-zero NOI, split by the direction of NOI. Of the 69 observations in the sample, 54 pertain to auctions where NOI was SELL after the first stage, while 15 pertain to auctions where NOI was BUY. This sample split includes both CDS and LCDS auctions. BUY NOI auctions have lower NOI amounts both on adjusted and unadjusted basis, they have higher recoveries in the final stage of the auction. BUY NOI auctions yield an average recovery of 52.6% and a median recovery of 52.5% compared to 32.3% and 22.6% respectively for SELL NOI auctions. However, BUY NOI auctions have much lower nominal ultimate recoveries with an average of 57.5% and a median of 52.4% compared to 65% and 72% respectively for SELL NOI auctions. Thus the difference between nominal ultimate recovery and auction recovery is also much lower for BUY NOI auctions at an average of 4.9% and median of 0.8% compared to 32.7% and 28.9% respectively for SELL NOI auctions. Even on an adjusted basis, the difference in recoveries for BUY NOI auctions is lower with an average of 0.3% and a median of -3.2%, when adjusting with the Altman-Kuehne Index, compared to 11.5% and 7.0% respectively for SELL NOI auctions. The difference between the two samples is larger when ultimate recoveries are adjusted by the High Yield index resulting in mean and median difference of -1.7% and -2.7% respectively for BUY NOI auctions compared to 14.0% and 10.0% respectively for SELL NOI auctions. Therefore, descriptive statistics provide preliminary evidence in support of Chernov, Gorbenko, and Makarov (2013)'s theoretical predictions about dealer incentives leading to equilibrium outcomes where a SELL NOI leads to auction recoveries that are lower than true value.

The trend outlined in Table 2 is robust to further splits in the sample by type of derivative instrument, as can be seen in Tables 3 and 4. CDS auctions with a BUY NOI have much lower mean and median differences in ultimate (both adjusted and unadjusted) and auction recoveries compared to SELL NOI auctions. Under the two adjustment measures, mean underrecovery in BUY NOI auctions is 1.7% and 4.2% compared to 13.5% and 18.4% for SELL NOI auctions. Median underrecovery is -5.7% and -3.5% for BUY NOI auctions compared to 9.5% and 14.8% for SELL NOI auctions. Similarly for the LCDS auctions the mean and median differences are lower for BUY NOI auctions compared to SELL NOI auctions.

While both measures of central tendency show that adjusted ultimate recoveries are lower than auction recoveries for BUY NOI auctions and higher for SELL NOI auctions, these might be driven by a few outliers. In order to understand the distribution of recovery variables, I plot histograms for the recovery variables in Figures 7 to 14. As before, the sample is split by NOI. The variables are unadjusted ultimate recovery, difference between unadjusted ultimate recovery and auction recovery, difference between Altman Adjusted ultimate recovery and auction recovery and lastly difference between high-yield adjusted ultimate recovery and auction recovery.

The distribution of unadjusted recoveries for SELL NOI auctions is skewed to the right (the mean is greater than the median) compared to BUY NOI auctions. This relative skew is larger in the distribution of differences between unadjusted ultimate and auction recoveries with the majority of BUY NOI observations being less than 10% while a majority of SELL NOI observations are above 10%. A similar trend (relative right skew for SELL NOI auctions) is visible for adjusted ultimate recoveries.

Next I use univariate methods to test for differences between pricing outcomes of BUY NOI and SELL NOI auctions. I calculate underrecovery for each of these samples as the difference between adjusted ultimate recovery and auction price. I use both the Altman Index and Barclays High Yield Index to adjust ultimate recovery which is estimated as the average ultimate recovery of all issues eligible for delivery. I then test for difference in means of underrecovery calculated for the BUY NOI and SELL NOI samples using pooled, Cochran and Satterthwaite tests. Results of these tests are outlined in Panel A of Table 5. Under the high-yield adjustment measure, means of the two distributions are different with 95% confidence, while under the Altman-adjusted measure, the means are different with 90% confidence. In line with descriptive results, univariate tests show that distributions of underrecoveries of BUY NOI and SELL NOI auctions are significantly different with underrecoveries for SELL NOI auctions being higher.

In order to account for scenarios where only issues with cheapest (lowest) ultimate recovery are delivered at the auction, I estimate underrecovery by using the lowest ultimate recovery among all issues eligible for delivery and run the same tests. Results outlined in Panel B of Table 5 show that under recoveries for SELL NOI auctions are significantly higher when the Barclays High Yield Index is used to adjust ultimate recovery.

This implies that CDS buyers receive a greater pay-off on their cash settled positions at the expense of CDS sellers when the first stage NOI is SELL and vice versa when it is BUY. The next section explores these differences through OLS regressions.

5.2 Empirical Results - Auction Bias

I primarily use cross sectional OLS regressions to test theoretical predictions about auction outcomes. The empirical implications of Chernov, Gorbenko, and Makarov (2013) are that both underpricing and overpricing equilibria are possible and for underpricing equilibria to be realized the final auction price should be a negative function of the NOI amount. I therefore test two hypotheses. The first hypothesis relates to the relationship between NOI and under or overrecovery and the second hypothesis relates to the relationship between degree of underpricing in the auction and the NOI amount. For reference, using secondary market prices, Chernov, Gorbenko, and Makarov (2013) show descriptively that, consistent with their theory, a SELL-NOI is positively correlated with underpricing. They also show that final auction price is negatively correlated to the NOI amount. I test these hypotheses independently using data on ultimate recoveries as well as bond prices.

I first test for the relationship between NOI (Buy or Sell) and the price discovered during the auction. I examine if the outcomes of the first stage lead to underrecovery. A statistically significant association between these two variables could imply that auction prices are systematically biased and are affected by first stage outcomes of the auction.

I regress ultimate recoveries on a binary variable that takes the value of 1 if the first stage NOI is a Sell and 0 otherwise. Given the fact that ultimate recoveries materialize an average of 20 months after CDS auction recoveries, I control for the passage of time and changes in state variables through an adjustment factor. The adjustment factor is derived from an index that proxies for passage of time and the change in state variables that can impact ultimate recovery during the period between the CDS auction date and ultimate recovery date. As described in the data section, I use the defaulted bond and loan indices from the Altman Kuehne Center and the Barclays High Yield Index for computing the adjustment factor. The adjustment factor is the ratio of the index values on the ultimate recovery date and the CDS auction date. I run separate regressions for each of the two adjustment factors.

Underrecovery as a dependant variable can be measured both as a difference and as a ratio between ultimate recovery and auction recovery. In the absence of theoretical or empirical insights on a suitable measure for underrecovery and to impart robustness to my results, I use both measures of recovery in several combinations to test their relationship with first stage auction outcomes. Specification 5, in which underrecovery is measured as a ratio of ultimate recovery to auction recovery and regressed on the NOI indicator and adjustment factor, is akin to specifications used for estimating abnormal returns. In this case, the underrecovery ratio is akin to realized return while the adjustment factor is akin to market return and the coefficient of the adjustment factor is therefore analogous to the beta on the market. In that sense, specification 5 allows for a "market beta" to be accounted for in the regressions and is more robust to errors emanating from assumptions pertaining to risk premium in other specifications. First stage auction outcomes have not been documented (either theoretically or empirically) to be related to firm specific and/or general economic factors and this minimizes the probability of bias and/or overestimated statistical power on account of omitted variables or multicollinearity. Moreover, since all specifications involve one measure of recovery being regressed on another measure of recovery for the same firm, I use no other control variable except for the adjustment factor.

$$\begin{aligned} NominalUltimateRecovery = \alpha + \beta * SELLDUMMY + \\ \theta * AuctionPrice + \tau * AdjustmentFactor + \epsilon \end{aligned} \tag{1}$$

$$\begin{aligned} NominalUltimateRecovery - AuctionPrice = \alpha + \beta * SELLDUMMY + \\ \tau * AdjustmentFactor + \epsilon \end{aligned} \tag{2}$$

$$\begin{aligned} NominalUltimateRecovery/AdjustmentFactor - AuctionPrice \\ = \alpha + \beta * SELLDUMMY + \epsilon \end{aligned} \tag{3}$$

$$\begin{aligned} (NominalUltimateRecovery/AdjustmentFactor)/AuctionPrice \\ = \alpha + \beta * SELLDUMMY + \epsilon \end{aligned} \tag{4}$$

$$
\begin{aligned}
&NominalUltimateRecovery/AuctionPrice \\
&= \alpha + \beta * SELLDUMMY + \theta * AdjustmentFactor + \epsilon
\end{aligned} \tag{5}
$$

Table 6 outlines the results of these regressions based on the Altman - Kuehne adjustment factor and Table 7 contains results using the Barclays High Yield Index adjustment factor. The variable of interest is SELLDUMMY. The coefficient of SELLDUMMY which proxies for SELL NOI auctions is positively associated with various measures of auction underrecovery for all specifications. The results hold irrespective of the adjustment factor used. For specification 5 which allows for a market beta to be estimated in the regression, results are significant when heteroskedasticity adjusted t statistics are estimated using White's method. Therefore, in auctions where the first stage outcome is SELL, the recovery rate at which CDS contracts are settled is significantly lower than the ultimate recovery on underlying credit securities: the auction is biased. Results from all specifications, for both adjustment factors, are robust to White's heteroskedasticity adjusted t-statistics. These findings are consistent with Chernov, Gorbenko, and Makarov (2013) who predict that CDS auctions misprice recoveries with auctions having a SELL NOI leading to underrecovery in the auction. These results do not support the analyses of Du and Zhu (2017) which predicts overrecovery for SELL NOI auctions and underrecovery for BUY NOI auctions.

Since multiple issues of the same underlying are eligible for delivery, I also examine the prices discovered at the auction in the context of the cheapest to deliver phenomenon. Theory does not examine linkages between the secondary markets and auction prices and is mute on cases where more than issue is eligible for delivery. Thus there are no theoretical predictions about the behavior of auction participants when multiple issues are eligible for delivery and one or more of them is "cheaper" than others.

Under the assumption that all agents have full knowledge of the ultimate recovery of all eligible issues and that secondary markets are able to impute these recoveries in traded prices with precision and supply of issues is unconstrained, the issue delivered in the auction will be the one with cheapest ultimate recovery. Thus under these assumptions, the issue with the lowest ultimate recovery for each firm is the true benchmark for auction recovery.

Accordingly, I use the lowest ultimate recovery among all eligible issues and run tests based on specifications 1 to 5. Table 8 and Table 9 outline results of these tests. While the results are in line with those in Table 6, they are weaker in significance. There are several reasons why weaker significance in these "cheapest to deliver" tests does not devalue conclusions drawn from the stronger results in Table 6. First, even under the assumption of full knowledge of ultimate recovery, my data shows that it is fairly restrictive to assume that secondary markets impute these recoveries with precision and that supply of these issues is friction less. There are 11 firms with heterogeneity in ultimate recovery among issues eligible for delivery. For 5 of these firms, the issue with the lowest ultimate recovery does not trade cheapest in the secondary markets prior to the auction. Thus the assumptions of price unbiasedness and frictionless trading, necessary for the the cheapest to deliver phenomenon to be in force at the auction do not seem to hold in my sample.

Second, it can be argued that even if the cheapest to deliver phenomenon is in force at the auction, it weakens the incentives of some agents to manipulate the auction for a higher payout on their CDS positions. For example, agents who are buyers of credit protection and hold none of the underlying issues or only hold issues other than the cheapest to deliver will earn a higher payout on their CDS position compared to the average recovery on all the underlying bonds if only the cheapest issue is delivered and priced correctly at the auction. Thus they have lower incentive to manipulate the auction and weaker evidence in support of auction bias in Tables 8 and 9 is entirely consistent with this assertion.

Next I investigate the second implication of Chernov, Gorbenko, and Makarov

(2013), final auction price should be a decreasing function of the NOI amount. This is critical for an empirical validation of auction bias under the Chernov, Gorbenko, and Makarov (2013) model since this negative relationship between auction price and the NOI amount is a necessary proxy for the holding constraint of auction participants which leads to underpricing in the auction. Since the NOI amount depends on the value of CDS contracts outstanding, Chernov, Gorbenko, and Makarov (2013) recommend scaling the NOI amount by either the net notional value of CDS contracts outstanding or the par value of all eligible credit securities. Due to unavailability of historical data on notional value of CDS contracts outstanding, I scale the NOI amount by outstanding par value of securities eligible for delivery. For greater robustness I use specifications with both scaled and unscaled NOI. Consistent with auction convention and previous literature, I sign SELL NOI amounts positive and BUY NOI amounts negative.

In addition, I also test for a positive relationship between the extent of underrecovery and the NOI amount. While this relationship is not predicted explicitly by theory, it is intuitively in line with proposition 4 of Chernov, Gorbenko, and Makarov (2013) whereby a larger NOI on account of submission of PSRs by agents with long CDS positions can depress the final auction price, increasing underrecovery. To impart robustness, I use several specifications to test these relationships.

$$AuctionPrice = \alpha + \beta * NOI + \epsilon \tag{6}$$

$$\begin{aligned}(NominalUltimateRecovery/AdjustmentFactor)/AuctionPrice \\ = \alpha + \beta * NOI + \epsilon\end{aligned} \tag{7}$$

$$NominalUltimateRecovery/AuctionPrice \\ = \alpha + \beta * NOI + \theta * AdjustmentFactor + \epsilon \tag{8}$$

$$NominalUltimateRecovery - AuctionPrice \\ = \alpha + \beta * NOI + \theta * AdjustmentFactor + \epsilon \tag{9}$$

$$(NominalUltimateRecovery/AdjustmentFactor) - AuctionPrice \\ = \alpha + \beta * NOI + \epsilon \tag{10}$$

$$AuctionPrice = \alpha + \beta * AdjustedNOI + \epsilon \tag{11}$$

$$(NominalUltimateRecovery/AdjustmentFactor)/AuctionPrice \\ = \alpha + \beta * AdjustedNOI + \epsilon \tag{12}$$

$$NominalUltimateRecovery/AuctionPrice \\ = \alpha + \beta * AdjustedNOI + \theta * AdjustmentFactor + \epsilon \tag{13}$$

$$NominalUltimateRecovery - AuctionPrice \\ = \alpha + \beta * AdjustedNOI + \theta * AdjustmentFactor + \epsilon \tag{14}$$

$$
\begin{aligned}
(NominalUltimateRecovery/AdjustmentFactor) - AuctionPrice \\
= \alpha + \beta * AdjustedNOI + \epsilon
\end{aligned} \tag{15}
$$

Specifications 6 and 7 test the second implication of Chernov, Gorbenko, and Makarov (2013) directly and are most pertinent for the existence of auction bias. Tables 10 and 11 show that consistent with theory, the auction price is negatively correlated with the NOI (specification 6) and scaled NOI amounts (specification 11). This result is unexpectedly significant for specification 6 which uses unscaled NOI, hinting at a strong relationship between the auction price and NOI amounts. These results support the theoretical precondition for realization of underpricing equilibria and auction bias.

In addition, specifications 7 to 10 test the relationship between various measures of underrecovery and unscaled NOI amounts. As expected there is no significant association between the two variables. Specifications 12 to 15 test the relationship between underrecovery and scaled NOI. Specification 13 closely resembles specification 5 and is similarly more robust than others in the sense that it allows for a market beta to be imputed in the regression. There is a significant positive association between underrecovery and NOI for specifications 12 and 13 thereby implying that higher NOI leads to lower auction prices which increases underrecovery and auction bias. Overall, these tests not only find evidence supporting underpricing in CDS auctions but also corroborate the theoretical channels through which underpricing equilibria are realized. These results hold with weaker significance when the cheapest to deliver phenomenon is accounted for in Table 12.

5.3 Empirical Results - Secondary Market Informativeness

I also employ a certainty equivalent based approach outlined by Altman, Resti, and Sironi (2004) to confirm these findings. I estimate certainty equivalents of ultimate recoveries and compare them to auction recoveries. The results are consistent with the findings of this section[18].

CDS auctions are conducted concurrent to trading of underlying bonds in secondary markets. Therefore, evidence supporting bias in CDS auctions motivates questions about the informativeness of bond prices vis a vis their ability to impute ultimate recoveries correctly. Given the endogeneity between bond trades and the auction, bond price informativeness may also be impacted by auction outcomes. If bond prices are informed, auction outcomes should be orthogonal to their relationship with ultimate recovery. However, a statistically significant association between auction outcomes and the relationship between ultimate recovery and bond prices may imply pricing bias in the bond market and/or price manipulation by auction participants.

I use three approaches to address the question of bond market informativeness in the context of CDS auctions. I use the heterogeneity in ultimate recovery of various issues of the same firm to verify if this heterogeneity is captured by bond prices in secondary markets. I also test if auction outcomes impact the relationship between bond prices and ultimate recovery. Lastly, conditional on the auction being biased, I test if recovery estimates based on bond prices are consistent with auction bias (as ultimate recoveries are).

Eleven firms have several issues eligible for delivery at the auction and many issues of the same firm have differing ultimate recovery values. In order to verify the informativeness of bond markets, I test if bond prices in secondary markets capture the heterogeneity in these ultimate recoveries which I adjust using the

[18] Appendix D contains a more detailed discussion.

Altman index. I form unique bond pairs from issues of the same firm and compute differences in their ultimate recoveries. Given the fact that bonds in default tend to be illiquid, it is likely that small differences in ultimate recovery between bond pairs are dwarfed by noise in secondary markets. Therefore, I exclude bond pairs with less than USD 5 difference in ultimate recovery. I then compute the average differences in the volume weighted prices of these bond pairs in 5 time intervals. These are ten days preceding the auction to 5 days preceding the auction, 5 days preceding the auction to auction day, auction day, auction day to 5 days following the auction and 5 days following the auction to ten days following the auction. I then regress pairwise differences in ultimate recovery on pairwise differences in bond prices for each of these intervals. If bond prices are fully informed, they will reflect the heterogeneity in ultimate recoveries. This means that while the coefficient on difference in bond prices will be significant, the intercept will equal zero as all the information about ultimate recovery is being reflected in bond prices. A statistically significant intercept implies that bond prices are unable to capture the heterogeneity in ultimate recoveries completely.

I outline results of these tests in Table 14. The intercept is insignificant when pairwise differences in ultimate recoveries are regressed on average pairwise differences in bond prices in the time intervals before the auction. However the intercept is large and significant on auction day and for time intervals after the auction. This seems to suggest that bond prices before the auction are more informed about differences in ultimate recovery than bond prices after the auction.

These results are supported by an alternative specification in Table 15 where I regress differences in ultimate recovery of these bond pairs on differences in their market price and an adjustment factor based on the Altman Index. The coefficient on differences in bond prices is positive and significant preceding the auction implying that secondary markets are informed about heterogeneity in ultimate recovery to some extent prior to the auction. However, the coefficient on price differences loses significance on the day of the auction and the time windows following it, implying that market prices are unable to impute the differences in ultimate recovery once the auction is over and become noisy estimates of ultimate recovery.

Next, I directly test the relationship between ultimate recoveries and bond prices in the context of the auction. If bond prices are informed about ultimate recovery, auction variables (which are theoretically independent of issue specific factors) should be orthogonal to the relationship between bond prices and ultimate recovery. I test for orthogonality of two auction variables, namely, SELL NOI and scaled NOI amount. I use volume weighted bond prices averaged over 5 different time intervals. They are ten days preceding the auction to auction date, 5 days preceding the auction to auction date, auction day, auction day to 5 days following the auction and auction day to 10 days following the auction. I use the following specifications:

$$NominalUltimateRecovery/BondPrice = \alpha + \beta * SELLNOIINDICATOR \\ + \theta * AdjustmentFactor + \epsilon \tag{16}$$

$$NominalUltimateRecovery/BondPrice = \alpha + \beta * SCALEDNOIAMOUNT \\ + \theta * AdjustmentFactor + \epsilon \tag{17}$$

Table 16 outlines the results of these regressions. Auction variables do not affect the relationship between bond prices and ultimate recovery prior to the auction. However bond prices are biased downward after the auction for SELL NOI auctions. The underpricing of ultimate recovery by bond prices after the auction is also significantly associated with the scaled NOI amount at the auction. Consistent with previous evidence, these results also suggest that bond prices are more informed estimates of ultimate recovery before the auction.

In order to further verify the difference in the informativeness of bond prices before and after the auction, I test for auction bias using bond prices as estimates of recovery. Bond prices as estimates of recovery are calculated for the same five time intervals as those in previous tests. Conditional on the knowledge that the auction is biased (evidence from ultimate recovery), if bond prices also show the auction to be biased in the same direction then they contain information about ultimate recovery. If however, bond prices do not reveal auction bias, then they are likely to be noisy or uninformed estimates of ultimate recovery. I use the following specification to test this hypothesis:

$$AuctionRecovery/BondPrice = \alpha + \beta * SELLNOIINDICATOR + \epsilon \quad (18)$$

Table 17 shows results for these tests. In line with the results from ultimate recoveries, SELL NOI auctions under-price recovery when recovery estimates are based on bond prices prior to the auction. However there is no evidence of bias in the auction when bond prices after the auction are used. Given that I have already established bias in auctions, these results suggest that, consistent with previous analyses, bond prices before the auction are more informed estimates of ultimate recovery than bond prices after the auction.

All three approaches used to evaluate the informativeness of the bond markets provide strong evidence in favor of bond prices before the auction being more informed. These results suggest that open CDS positions (before the auction) enrich the information environment in secondary markets for bonds in default leading to prices that are more informative of ultimate recovery.

6 Conclusion

CDS settlement auctions were developed because of concerns of manipulation of secondary markets by CDS traders. It is therefore incomplete to assess the efficiency of these auctions by benchmarking them to secondary markets. Efficiency of this settlement mechanism has far reaching consequences both for the pricing of credit default swaps as well as for market integrity. Several theorists have analyzed the auction based settlement mechanism and predicted a systematic bias which undermines efficient discovery of the recovery rate in these auctions. Theorists have also outlined several economic mechanisms through which bias manifests itself in the auction price. Two major theories analyzing CDS auctions in the literature have contrasting predictions about the direction of the bias. Most empirical studies have used secondary market data to descriptively examine the efficiency of the auction mechanism. A key challenge in analyzing these auctions empirically lies in establishing a reliable benchmark for auction recoveries.

I establish this benchmark by using hand-collected data on ultimate recoveries from bankruptcy and SEC filings. I provide evidence to support bias and inefficiency in CDS auctions. Empirical tests suggest, on average, CDS auctions lead to underpricing of recoveries. This underpricing is correlated to first stage outcomes of the auction. I provide evidence in support of the hypothesis that under recoveries are more severe in cases where the first stage auction NOI is SELL and are increasing in the NOI amount. Further tests reveal a negative relationship between auction-prices and NOI amounts. Therefore, I find empirical evidence in support of Chernov, Gorbenko, and Makarov (2013) which states that underpricing equilibria can arise with a SELL NOI so long as underpricing is increasing in the NOI amount and auction-price is decreasing in the NOI amount. These results do not support the predictions of Du and Zhu (2017) which envisage underpricing in BUY NOI auctions and vice-versa. These results are robust to several empirical specifications and an alternate certainty equivalent based approach.

I also investigate the informativeness of bond prices vis-a-vis ultimate recovery in the context of CDS auctions. I use three approaches to test for bond price efficiency and results from all three sets of tests suggest that bond prices before the auction are more informed about ultimate recovery and become noisier after the auction. This suggests that the existence of open CDS positions enriches the information environment for bonds and reduces bias in their pricing.

Table 1: Summary Statistics - All Auctions

All Auctions

Variable	N	Mean	Median	Min	Max	Std Dev
Par Amount of Physical Settlement Requests	69	195.21	46.83	1.23	4920.00	612.79
Physical settlement requests scaled by claim outstanding	69	0.09	0.03	0.00	0.60	0.14
Auction Price	69	0.37	0.24	0.02	0.98	0.30
Ultimate Recovery (Nominal/Unadjusted)	69	0.63	0.67	0.00	1.22	0.38
Nominal Ultimate Recovery minus Auction Price	69	0.27	0.23	-0.41	1.05	0.33
Altman Adjusted Ultimate Recovery minus Auction Price	69	0.09	0.06	-0.37	0.84	0.22
HY Index Adjusted Ultimate Recovery minus Auction Price	69	0.11	0.07	-0.45	0.83	0.25
Time to ultimate recovery (in days)	69	619.70	539	20	2790	543.45
Number of deliverables at the auction	69	9.87	4	1	302	35.79

Table 2: Summary Statistics by NOI

BUY NOI Auctions

Variable	**N**	**Mean**	**Median**	**Min**	**Max**	**Std Dev**
Par Amount of Physical Settlement Requests	15	74.77	30.50	3.00	529.10	131.96
Physical settlement requests scaled by claim outstanding	15	0.03	0.02	0.00	0.12	0.03
Auction Price	15	0.53	0.53	0.08	0.97	0.33
Ultimate Recovery (Nominal/Unadjusted)	15	0.58	0.52	0.00	1.22	0.39
Nominal Ultimate Recovery minus Auction Price	15	0.05	0.01	-0.41	0.77	0.29
Altman Adjusted Ultimate Recovery minus Auction Price	15	0.00	-0.03	-0.37	0.52	0.24
HY Index Adjusted Ultimate Recovery minus Auction Price	15	-0.02	-0.03	-0.45	0.57	0.25
Time to ultimate recovery (in days)	15	481.13	430	62	960	275.04
Number of deliverables at the auction	15	6.13	4	2	21	5.38

SELL NOI Auctions

Variable	**N**	**Mean**	**Median**	**Min**	**Max**	**Std Dev**
Par Amount of Physical Settlement Requests	54	228.67	49.15	1.23	4920.00	686.98
Physical settlement requests scaled by claim outstanding	54	0.10	0.04	0.00	0.60	0.15
Auction Price	54	0.32	0.22	0.02	0.98	0.28
Ultimate Recovery (Nominal/Unadjusted)	54	0.65	0.72	0.00	1.20	0.38
Nominal Ultimate Recovery minus Auction Price	54	0.33	0.29	-0.35	1.05	0.32
Altman Adjusted Ultimate Recovery minus Auction Price	54	0.11	0.07	-0.36	0.84	0.22
HY Index Adjusted Ultimate Recovery minus Auction Price	54	0.14	0.10	-0.38	0.83	0.24
Time to ultimate recovery (in days)	54	656.24	565	20	2790	597.93
Number of deliverables at the auction	54	11	3	1	302	40.67

Table 3: Summary Statistics- CDS Auctions

BUY NOI Auctions

Variable	**N**	**Mean**	**Median**	**Min**	**Max**	**Std Dev**
Par Amount of Physical Settlement Requests	7	118.72	61.16	6.25	529.10	184.66
Physical settlement requests scaled by claim outstanding	7	0.04	0.03	0.00	0.12	0.04
Auction Price	7	0.31	0.24	0.13	0.71	0.22
Ultimate Recovery (Nominal/Unadjusted)	7	0.42	0.51	0.00	1.00	0.37
Nominal Ultimate Recovery minus Auction Price	7	0.11	0.01	-0.32	0.77	0.37
Altman Adjusted Ultimate Recovery minus Auction Price	7	0.02	-0.06	-0.32	0.52	0.29
HY Index Adjusted Ultimate Recovery minus Auction Price	7	0.04	-0.04	-0.32	0.57	0.32
Time to ultimate recovery (in days)	7	512.42	441	347	769	347
Number of deliverables at the auction	7	9.14	7	2	21	6.81

SELL NOI Auctions

Variable	**N**	**Mean**	**Median**	**Min**	**Max**	**Std Dev**
Par Amount of Physical Settlement Requests	37	317.77	98.74	1.23	4920.00	817.55
Physical settlement requests scaled by claim outstanding	37	0.14	0.06	0.00	0.60	0.17
Auction Price	37	0.20	0.16	0.02	0.75	0.19
Ultimate Recovery (Nominal/Unadjusted)	37	0.54	0.47	0.00	1.20	0.37
Nominal Ultimate Recovery minus Auction Price	37	0.34	0.33	-0.35	1.05	0.35
Altman Adjusted Ultimate Recovery minus Auction Price	37	0.14	0.10	-0.36	0.84	0.23
HY Index Adjusted Ultimate Recovery minus Auction Price	37	0.18	0.15	-0.38	0.83	0.26
Time to ultimate recovery (in days)	37	753.32	587	20	2790	662.87
Number of deliverables at the auction	37	14.6	5	1	302	48.91

Table 4: Summary Statistics- LCDS Auctions

BUY NOI Auctions

Variable	N	Mean	Median	Min	Max	Std Dev
Par Amount of Physical Settlement Requests	8	36.31	24.25	3.00	141.00	44.47
Physical settlement requests scaled by claim outstanding	8	0.02	0.01	0.00	0.04	0.01
Auction Price	8	0.71	0.81	0.08	0.97	0.30
Ultimate Recovery (Nominal/Unadjusted)	8	0.71	0.77	0.08	1.22	0.38
Nominal Ultimate Recovery minus Auction Price	8	0.00	0.01	-0.41	0.26	0.20
Altman Adjusted Ultimate Recovery minus Auction Price	8	-0.01	-0.03	-0.37	0.35	0.20
HY Index Adjusted Ultimate Recovery minus Auction Price	8	-0.07	-0.02	-0.45	0.10	0.18
Time to ultimate recovery (in days)	8	453.75	328.5	62	960	353.36
Number of deliverables at the auction	8	3.5	3	2	5	1.06

SELL NOI Auctions

Variable	N	Mean	Median	Min	Max	Std Dev
Par Amount of Physical Settlement Requests	17	34.74	23.00	2.00	138.00	32.87
Physical settlement requests scaled by claim outstanding	17	0.03	0.01	0.00	0.20	0.05
Auction Price	17	0.59	0.65	0.10	0.98	0.27
Ultimate Recovery (Nominal/Unadjusted)	17	0.88	1.00	0.01	1.17	0.29
Nominal Ultimate Recovery minus Auction Price	17	0.29	0.25	-0.11	0.72	0.25
Altman Adjusted Ultimate Recovery minus Auction Price	17	0.07	-0.02	-0.16	0.41	0.17
HY Index Adjusted Ultimate Recovery minus Auction Price	17	0.05	0.03	-0.21	0.41	0.15
Time to ultimate recovery (in days)	17	444.94	257	28	1425	355.52
Number of deliverables at the auction	17	3.11	3	1	6	1.45

Table 5: Difference in Underrecovery at SELL NOI and BUY NOI Auctions.

Differences in the means of auction underrecovery between SELL-NOI and BUY-NOI auction samples. Underrecovery is calculated as the difference between adjusted ultimate recovery and auction price. Ultimate recovery is adjusted using the Altman-Kuehne Index and the Bloomberg Barclays High Yield Index. In Panel A, ultimate recovery is estimated as the average ultimate recovery of all issues eligible for delivery. In Panel B, ultimate recovery is estimated as the cheapest ultimate recovery among all eligible issues. Tests are run using the pooled, Satterthwaite and Cochran methods. Satterthwaite and Cochran tests assume that the variances of the two samples are not equal.

Panel A:

Method	**Altman Adjusted**	**HY Index Adjusted**
Pooled	1.83*	2.33**
Satterthwaite	1.74*	2.27**
Cochran	1.74*	2.27**

Panel B:

Method	**Altman Adjusted**	**HY Index Adjusted**
Pooled	1.29	1.81*
Satterthwaite	1.28	1.82*
Cochran	1.28	1.82*

*,**,*** represent significance at 90%, 95% and 99% confidence respectively.

Table 6: OLS Regressions for Auction Underrecovery - Altman-Kuehne Index

OLS regressions based on equations 1 -5:

$$NominalUltimateRecovery = \alpha + \beta * SELLDUMMY + \theta * AuctionPrice + \tau * AdjustmentFactor + \epsilon \tag{1}$$

$$NominalUltimateRecovery - AuctionPrice = \alpha + \beta * SELLDUMMY + \tau * AdjustmentFactor + \epsilon \tag{2}$$

$$NominalUltimateRecovery/AdjustmentFactor - AuctionPrice = \alpha + \beta * SELLDUMMY + \epsilon \tag{3}$$

$$(NominalUltimateRecovery/AdjustmentFactor)/AuctionPrice = \alpha + \beta * SELLDUMMY + \epsilon \tag{4}$$

$$NominalUltimateRecovery/AuctionPrice = \alpha + \beta * SELLDUMMY + \theta * AdjustmentFactor + \epsilon \tag{5}$$

T-statistics are in parentheses. Square brackets contain White's heteroskedasticity adjusted t-statistics. The regressand is auction underrecovery. The regressors are: A binary variable which takes the value of one if the auction has a SELL NOI and 0 otherwise, price discovered in the auction, an adjustment factor based on the Altman-Kuehne Defaulted Bonds and Loan Index.

	1	2	3	4	5
Intercept	-0.23 (1.44) [1.38]	-0.24 (2.20)** [2.40]**	-0.00 (.01) [.01]	1.01 (2.20)** [5.30]***	-3.13 (2.46)** [2.71]***
Sell Dummy	0.20 (2.36)** [2.23]**	0.21 (2.45)** [2.27]**	0.11 (1.79)* [1.78]*	1.05 (2.00)** [3.10]***	1.34 (1.40) [2.18]**
Auction Price	0.98 (7.20)*** [8.06]***				
Adjustment factor	0.23 (2.97)*** [2.77]***	0.23 (3.42)*** [3.33]***			3.39 (4.41)*** [3.76]***
Adjusted R Squared	0.42	0.24	0.03	0.04	0.25
Observations	70	70	70	70	70

Table 7: OLS Regressions for Auction Underrecovery - Bloomberg Barclays High Yield Index

OLS regressions based on equations 1 -5:

$$NominalUltimateRecovery = \alpha + \beta * SELLDUMMY + \theta * AuctionPrice + \tau * AdjustmentFactor + \epsilon \tag{1}$$

$$NominalUltimateRecovery - AuctionPrice = \alpha + \beta * SELLDUMMY + \tau * AdjustmentFactor + \epsilon \tag{2}$$

$$NominalUltimateRecovery/AdjustmentFactor - AuctionPrice = \alpha + \beta * SELLDUMMY + \epsilon \tag{3}$$

$$(NominalUltimateRecovery/AdjustmentFactor)/AuctionPrice = \alpha + \beta * SELLDUMMY + \epsilon \tag{4}$$

$$NominalUltimateRecovery/AuctionPrice = \alpha + \beta * SELLDUMMY + \theta * AdjustmentFactor + \epsilon \tag{5}$$

T-statistics are in parentheses. Square brackets contain White's heteroskedasticity adjusted t-statistics. The regressand is auction underrecovery. The regressors are: A binary variable which takes the value of one if the auction has a SELL NOI and 0 otherwise, price discovered in the auction, an adjustment factor based on the Bloomberg Barclays High Yield Bond Index.

	1	2	3	4	5
Intercept	-0.20 (1.17) [1.30]	-0.29 (2.08)** [2.51]**	-0.02 (.34) [.33]	1.02 (1.80)* [4.47]***	-3.58 (2.17)** [2.00]**
Sell Dummy	0.21 (2.27)** [2.25]**	0.22 (2.54)** [2.49]**	0.16 (2.36)** [2.36]**	1.32 (2.06)** [3.31]***	1.56 (1.52) [2.75]***
Auction Price	0.89 (6.83)*** [8.43]***				
Adjustment factor	0.25 (2.47)** [2.99]***	0.27 (2.83)*** [3.51]***			3.90 (3.44)*** [2.69]***
Adjusted R Squared	0.39	0.20	0.05	0.04	0.18
Observations	70	70	70	70	70

*, ** and *** represent significance at 90%, 95% and 99% confidence respectively.

Table 8: Auction Underrecovery using Cheapest to Deliver Issues - Altman-Kuehne Index

OLS regressions based on equations 1 -5 using lowest ultimate recovery among all issues eligible for delivery at each auction:

$$\begin{aligned} NominalUltimateRecovery = \alpha + \beta * SELLDUMMY + \\ \theta * AuctionPrice + \tau * AdjustmentFactor + \epsilon \end{aligned} \tag{1}$$

$$\begin{aligned} NominalUltimateRecovery - AuctionPrice = \alpha + \beta * SELLDUMMY + \\ \tau * AdjustmentFactor + \epsilon \end{aligned} \tag{2}$$

$$\begin{aligned} NominalUltimateRecovery/AdjustmentFactor - AuctionPrice \\ = \alpha + \beta * SELLDUMMY + \epsilon \end{aligned} \tag{3}$$

$$\begin{aligned} (NominalUltimateRecovery/AdjustmentFactor)/AuctionPrice \\ = \alpha + \beta * SELLDUMMY + \epsilon \end{aligned} \tag{4}$$

$$\begin{aligned} NominalUltimateRecovery/AuctionPrice \\ = \alpha + \beta * SELLDUMMY + \theta * AdjustmentFactor + \epsilon \end{aligned} \tag{5}$$

T-statistics are in parentheses. Square brackets contain White's heteroskedasticity adjusted t-statistics. The regressand is auction underrecovery. The regressors are: A binary variable which takes the value of one if the auction has a SELL NOI and 0 otherwise, price discovered in the auction, an adjustment factor based on the Altman-Kuehne Defaulted Bonds and Loan Index.

	1	2	3	4	5
	-0.22	-.24	0.00	.96	-2.33
Intercept	(1.25)	(1.93)*	(0.09)	(2.29)**	(2.01)**
	[1.32]	[2.15]**	[0.01]	[4.43]***	[2.06]**
	.17	.17	.08	.80	1.12
SELLDUMMY	(1.82)*	(1.90)*	(1.29)	(1.70)*	(1.29)
	[1.76]*	[1.83]*	[1.32]	[2.49]**	[1.95]*
	0.98				
Auction Price	(6.58)***				
	[7.84]***				
	.21	.21			2.67
Adjustment factor	(2.48)***	(2.88)***			(3.88)***
	[2.55]***	[2.90]***			[3.07]***
Adjusted R Squared	0.37	0.16	0.00	0.02	0.21
Observations	70	70	70	70	70

Table 9: Auction Underrecovery using Cheapest to Deliver Issues - Bloomberg Barclays High Yield Index

OLS regressions based on equations 1 -5 using lowest ultimate recovery among all issues eligible for delivery at each auction:

$$\begin{aligned} NominalUltimateRecovery = \alpha + \beta * SELLDUMMY + \\ \theta * AuctionPrice + \tau * AdjustmentFactor + \epsilon \end{aligned} \tag{1}$$

$$\begin{aligned} NominalUltimateRecovery - AuctionPrice = \alpha + \beta * SELLDUMMY + \\ \tau * AdjustmentFactor + \epsilon \end{aligned} \tag{2}$$

$$\begin{aligned} NominalUltimateRecovery/AdjustmentFactor - AuctionPrice \\ = \alpha + \beta * SELLDUMMY + \epsilon \end{aligned} \tag{3}$$

$$\begin{aligned} (NominalUltimateRecovery/AdjustmentFactor)/AuctionPrice \\ = \alpha + \beta * SELLDUMMY + \epsilon \end{aligned} \tag{4}$$

$$\begin{aligned} NominalUltimateRecovery/AuctionPrice \\ = \alpha + \beta * SELLDUMMY + \theta * AdjustmentFactor + \epsilon \end{aligned} \tag{5}$$

T-statistics are in parentheses. Square brackets contain White's heteroskedasticity adjusted t-statistics. The regressand is auction underrecovery. The regressors are: A binary variable which takes the value of one if the auction has a SELL NOI and 0 otherwise, price discovered in the auction, an adjustment factor based on the Bloomberg Barclays High Yield Bond Index.

	1	2	3	4	5
Intercept	-0.17 (.91) [1.07]	-.26 (1.71)* [2.01]**	-.02 (.42) [.44]	.97 (2.13)** [4.10]***	-3.22 (2.28)** [1.78]*
SELLDUMMY	.17 (1.74)* [1.77]*	.18 (1.98)* [2.03]**	.13 (1.81)* [1.88]*	1.03 (1.94)* [2.84]***	1.16 (1.32) [2.35]**
Auction Price	0.89 (6.33)*** [7.99]***				
Adjustment factor	.21 (1.98)* [2.37]**	.24 (2.29)** [2.66]***			3.54 (3.65)*** [2.42]**
Adjusted R Squared	0.35	0.12	0.03	0.04	0.19
Observations	70	70	70	70	70

*, ** and *** represent significance at 90%, 95% and 99% confidence respectively.

Table 10: OLS Regressions of Auction Underrecovery on NOI amount

OLS regressions based on equations 6 -10:

$$AuctionPrice = \alpha + \beta * NOI + \epsilon \tag{6}$$

$$\begin{aligned}(NominalUltimateRecovery/AdjustmentFactor)/AuctionPrice \\ = \alpha + \beta * NOI + \epsilon\end{aligned} \tag{7}$$

$$\begin{aligned}NominalUltimateRecovery/AuctionPrice \\ = \alpha + \beta * NOI + \theta * AdjustmentFactor + \epsilon\end{aligned} \tag{8}$$

$$\begin{aligned}NominalUltimateRecovery - AuctionPrice \\ = \alpha + \beta * NOI + \theta * AdjustmentFactor + \epsilon\end{aligned} \tag{9}$$

$$\begin{aligned}(NominalUltimateRecovery/AdjustmentFactor) - AuctionPrice \\ = \alpha + \beta * NOI + \epsilon\end{aligned} \tag{10}$$

T-statistics are in parentheses. Square brackets contain White's heteroskedasticity adjusted t-statistics. The regressand is auction underrecovery. The regressors are - NOI amount in the auction and an adjustment factor based on the Altman-Kuehne Defaulted Bonds and Loan index.

	6	7	8	9	10
	38.43	1.75	-2.48	-.14	-.90
Intercept	(10.20)***	(7.34)***	(2.03)**	(1.34)	(3.14)***
	[10.36]***	[8.29]***	[2.19]**	[1.38]	[3.17]***
	-.01	0.00	0.00	.00	.00
NOI Amount	(1.45)	(1.05)	(.73)	(.23)	(0.25)
	[2.76]***	[1.34]	[1.01]	[.68]	[0.91]
			3.58	.27	
Adjustment factor			(4.66)***	(3.92)***	
			[4.01]***	[4.05]***	
Adjusted R Squared	0.01	0.00	0.24	0.16	0
Observations	70	70	70	70	70

Table 11: OLS Regressions of Auction Underrecovery on Scaled NOI amount

OLS regressions based on equations 11-15:

$$AuctionPrice = \alpha + \beta * AdjustedNOI + \epsilon \tag{11}$$

$$\begin{aligned}(NominalUltimateRecovery/AdjustmentFactor)/AuctionPrice \\ = \alpha + \beta * AdjustedNOI + \epsilon\end{aligned} \tag{12}$$

$$\begin{aligned}NominalUltimateRecovery/AuctionPrice \\ = \alpha + \beta * AdjustedNOI + \theta * AdjustmentFactor + \epsilon\end{aligned} \tag{13}$$

$$\begin{aligned}NominalUltimateRecovery - AuctionPrice \\ = \alpha + \beta * AdjustedNOI + \theta * AdjustmentFactor + \epsilon\end{aligned} \tag{14}$$

$$\begin{aligned}(NominalUltimateRecovery/AdjustmentFactor) - AuctionPrice \\ = \alpha + \beta * AdjustedNOI + \epsilon\end{aligned} \tag{15}$$

T-statistics are in parentheses. Square brackets contain White's heteroskedasticity adjusted t-statistics. The regressand is auction underrecovery. The regressors are - NOI scaled by claims outstanding and an adjustment factor based on the Altman-Kuehne Defaulted Bonds and Loan Index.

	11	12	13	14	15
Intercept	41.82 (10.75)*** [10.29]***	1.42 (6.04)*** [7.32]***	-2.27 (2.02)** [2.19]**	-.1426 (1.28) [1.33]	-.0746 (2.44)** [2.31]***
Adj NOI Amount	-78.74 (3.13)*** [5.31]***	5.38 (3.67)*** [2]**	9.51 (3.61)*** [1.79]*	.283 (1.09) [1.02]	.236 (1.25) [1.29]
Adjustment factor			3.04 (4.22)*** [4.15]***	.2543 (3.59)*** [3.7]***	
Adjusted R Squared	0.1	0.15	0.36	0.17	0.00
Observations	70	70	70	70	70

*, ** and *** represent significance at 90%, 95% and 99% confidence respectively.

Table 12: OLS Regressions of Auction Underrecovery using Cheapest to Deliver Issues on NOI amount

OLS regressions based on equations 7 -10:

$$(NominalUltimateRecovery/AdjustmentFactor)/AuctionPrice \\ = \alpha + \beta * NOI + \epsilon \tag{7}$$

$$NominalUltimateRecovery/AuctionPrice \\ = \alpha + \beta * NOI + \theta * AdjustmentFactor + \epsilon \tag{8}$$

$$NominalUltimateRecovery - AuctionPrice \\ = \alpha + \beta * NOI + \theta * AdjustmentFactor + \epsilon \tag{9}$$

$$(NominalUltimateRecovery/AdjustmentFactor) - AuctionPrice \\ = \alpha + \beta * NOI + \epsilon \tag{10}$$

T-statistics are in parentheses. Square brackets contain White's heteroskedasticity adjusted t-statistics. The regressand is auction underrecovery. The regressors are - NOI amount in the auction and an adjustment factor based on the Altman-Kuehne Defaulted Bonds and Loan index.

	7	8	9	10
	1.52	-1.72	-15.13	6.26
Intercept	(7.46)***	(1.60)	(1.27)	(2.98)**
	[8.53]***	[1.60]	[1.33]	[2.17]**
	0.00	0.00	.00	0.00
NOI Amount	(1.40)	(1.24)	(0.02)	(0.17)
	[1.48]	[1.27]	[0.04]	[0.36]
		2.77	24.56	
Adjustment factor		(4.11)***	(3.30)***	
		[3.34]***	[3.43]***	
Adjusted R Squared	0.01	0.20	0.11	0
Observations	70	70	70	70

Table 13: OLS Regressions of Auction Underrecovery using Cheapest to Deliver Issues on Scaled NOI amount

OLS regressions based on equations 12-15:

$$\begin{aligned}(NominalUltimateRecovery/AdjustmentFactor)/AuctionPrice \\ = \alpha + \beta * AdjustedNOI + \epsilon\end{aligned} \tag{12}$$

$$\begin{aligned}NominalUltimateRecovery/AuctionPrice \\ = \alpha + \beta * AdjustedNOI + \theta * AdjustmentFactor + \epsilon\end{aligned} \tag{13}$$

$$\begin{aligned}NominalUltimateRecovery - AuctionPrice \\ = \alpha + \beta * AdjustedNOI + \theta * AdjustmentFactor + \epsilon\end{aligned} \tag{14}$$

$$\begin{aligned}(NominalUltimateRecovery/AdjustmentFactor) - AuctionPrice \\ = \alpha + \beta * AdjustedNOI + \epsilon\end{aligned} \tag{15}$$

T-statistics are in parentheses. Square brackets contain White's heteroskedasticity adjusted t-statistics. The regressand is auction underrecovery. The regressors are - NOI scaled by claims outstanding and an adjustment factor based on the Altman-Kuehne Defaulted Bonds and Loan Index.

	12	13	14	15
	1.21	0.72	-14.26	4.27
Intercept	(5.99)***	(1.31)	(1.21)	(1.33)
	[6.7]***	[1.26]	[1.28]	[1.26]
	5.16	4.87	37.07	28.32
Adj NOI Amount	(4.11)***	(3.76)***	(1.35)	(1.42)
	[1.92]*	[1.82]*	[1.32]	[1.53]
		0.33	22.16	
Adjustment factor		(0.94)	(2.95)***	
		[0.94]	[3.14]***	
Adjusted R Squared	0.19	0.19	0.14	0.1
Observations	70	70	70	70

*, ** and *** represent significance at 90%, 95% and 99% confidence respectively.

Table 14: OLS Regression of pairwise differences in ultimate recovery on pairwise differences in bond prices.

Regressions of pairwise differences in the ultimate recoveries of various issues of the same underlying firm on pairwise differences in the prices of those issues in secondary markets. Ultimate recoveries are adjusted using the Altman-Kuehne Index. Pairwise differences in bond prices are estimated as difference in volume weighted prices of issues of the same underlying firm. The tests are run for bond price samples from five different time windows around the auction date. Each column contains results for the test run for the time window specified in the column heading.

Variable	10 days prior to 5 days prior to auction	5 days prior, to auction date	Auction Day	Auction date to 5 days after	5 days after auction to 10 days after
Intercept	-.14 (.06)	1.04 (.54)	4.67 (2.71)***	5.6 (2.4)***	3.43 (1.68)*
Price Difference	1.86 (6.2)***	1.71 (8.8)***	.81 (2.7)***	1.24 (3.45)***	1.43 (3.61)***
Adjusted R Squared	0.64	0.78	0.28	0.13	0.23
Observations	72	67	53	85	85

*, ** and *** represent significance at 90%, 95% and 99% confidence respectively.

Table 15: OLS Regression of pairwise differences in ultimate recovery on pairwise differences in bond prices.

Differences in the ultimate recoveries of various issues of the same underlying firm are regressed on pairwise differences in the prices of those issues in secondary markets and an adjustment factor based on the Altman-Kuehne Index. Pairwise differences in bond prices are estimated as difference in volume weighted prices of issues of the same underlying firm. The tests are run for bond price samples from five different time windows around the auction date. Each column contains results for the test run for the time window specified in the column heading.

Variable	10 days prior to 5 days prior to auction	5 days prior, to auction date	Auction Day	Auction date to 5 days after	5 days after auction to 10 days after
Intercept	-20.43 (0.85)	-52.4 (4.39)***	75.56 (7.21)***	23.44 (1.32)	50.96 (2.60)**
Price Difference	2.29 (3.15)***	3.74 (6.98)***	-0.52 (1.34)	1.06 (1.34)	-0.28 (0.61)
Adjustment Factor	13.77 (0.83)	25.28 (5.29)***	-36.54 (7.01)***	-7.77 (0.78)	-19.54 (1.86)*
Adjusted R Squared	0.15	0.71	0.46	0.30	0.14
Observations	72	67	53	85	85

*, ** and *** represent significance at 90%, 95% and 99% confidence respectively.

Table 16: Ultimate recovery and Bond Prices.

Regressions of ultimate recoveries on bond prices and auction outcomes.The regressand is the ratio of ultimate recovery and volume weighted bond prices of all bonds eligible for delivery at each auction. The regressors are- A binary variable which takes the value of one if the auction has a SELL NOI and 0 otherwise (Panel A), the NOI scaled by claims outstanding (Panel B) and an adjustment factor based on the Altman Defaulted bonds and loan index. Panel A shows results for specification 16 and panel B shows results for specification 17. Bond prices are estimated as volume weighted prices for five different time windows. Each column contains results for the subsample pertaining to the time window specified in the column heading.

Panel A: Specification 16

Variable	10 days prior, to Auction day	5 days prior, to auction date	Auction Day	Auction date to 5 days after	Auction day to 10 days after
Intercept	-0.8 (.93)	-0.7 (.8)	-1.3 (1.44)	-1.4 (1.57)	-1.1 (1.26)
SELL NOI Indicator	0.7 (1.03)	0.8 (1.03)	1.29 (1.74)*	1.27 (1.72)*	1.13 (1.7)*
Adjustment Factor	1.5 (4.11)***	1.4 (3.68)***	1..81 (3.86)***	1.86 (4.25)***	1.67 (4.11)***
Adjusted R Squared	0.24	0.19	0.24	0.27	0.24
Observations	42	41	42	42	42

Panel B: Specification 17

Variable	10 days prior, to Auction day	5 days prior, to auction date	Auction Day	Auction date to 5 days after	Auction day to 10 days after
Intercept	-.4 (.65)	-.02 (.4)	-.63 (.89)	-.69 (1.03)	-.5 (.77)
Scaled NOI Amount	2.5 (1.18)	2.1 (1.1)	4.7 (1.71)*	4.3 (1.77)*	4.1 (1.79)*
Adjustment Factor	1.43 (4.16)***	1.4 (3.53)***	1.7 (3.82)***	1.77 (4.19)***	1.58 (3.91)***
Adjusted R Squared	0.29	0.22	0.32	0.34	0.31
Observations	42	41	42	42	42

*, ** and *** represent significance at 90%, 95% and 99% confidence respectively.

Table 17: Bond Prices and Auction Recovery.

Regressions of the ratio of auction price to bond prices on an indicator variable which takes the value of 1 if the auction NOI is SELL and 0 otherwise. Bond prices are estimated as volume weighted prices for five different time windows. Each column contains results for the subsample pertaining to the time window specified in the column heading.

Variable	10 days prior, to Auction day	5 days prior, to auction date	Auction Day	Auction date to 5 days after	Auction day to 10 days after
Intercept	.99 (8.55)***	1.01 (8.56)***	.95 (10.9)***	.96 (10.6)***	.95 (9.51)*
SELL NOI Indicator	-0.27 (2.21)**	-0.28 (2.29)**	-.08 (0.9)	-.0 (0.96)	-.13 (1.26)
Adjusted R Squared	0.11	0.12	0.001	0.009	0.03
Observations	42	41	42	42	42

*, ** and *** represent significance at 90%, 95% and 99% confidence respectively.

Figure 1: Scatter plot of bond price on auction day and auction price for all auctions

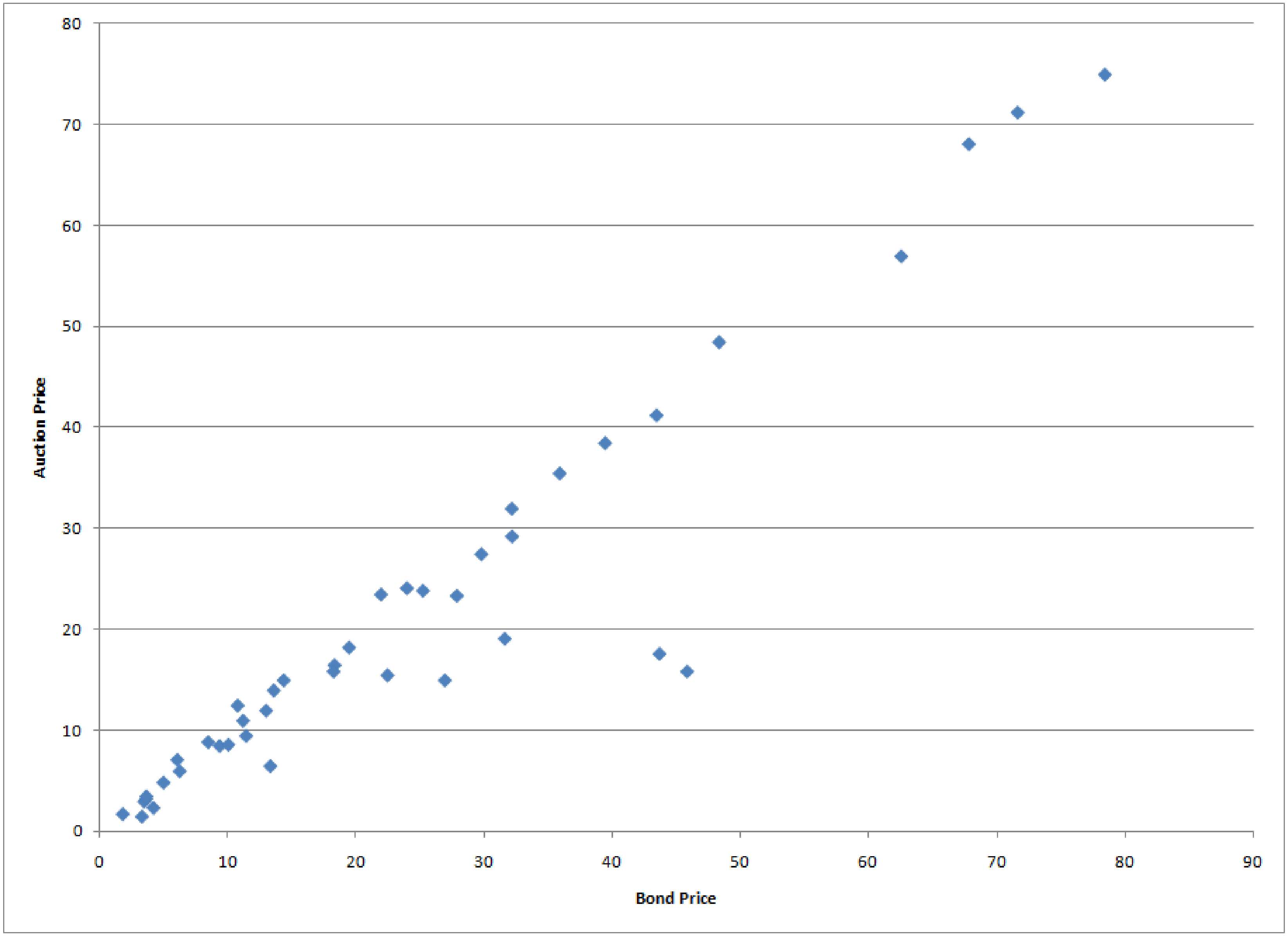


Figure 2: Scatter plot of bond price on auction day and auction price for SELL NOI auctions

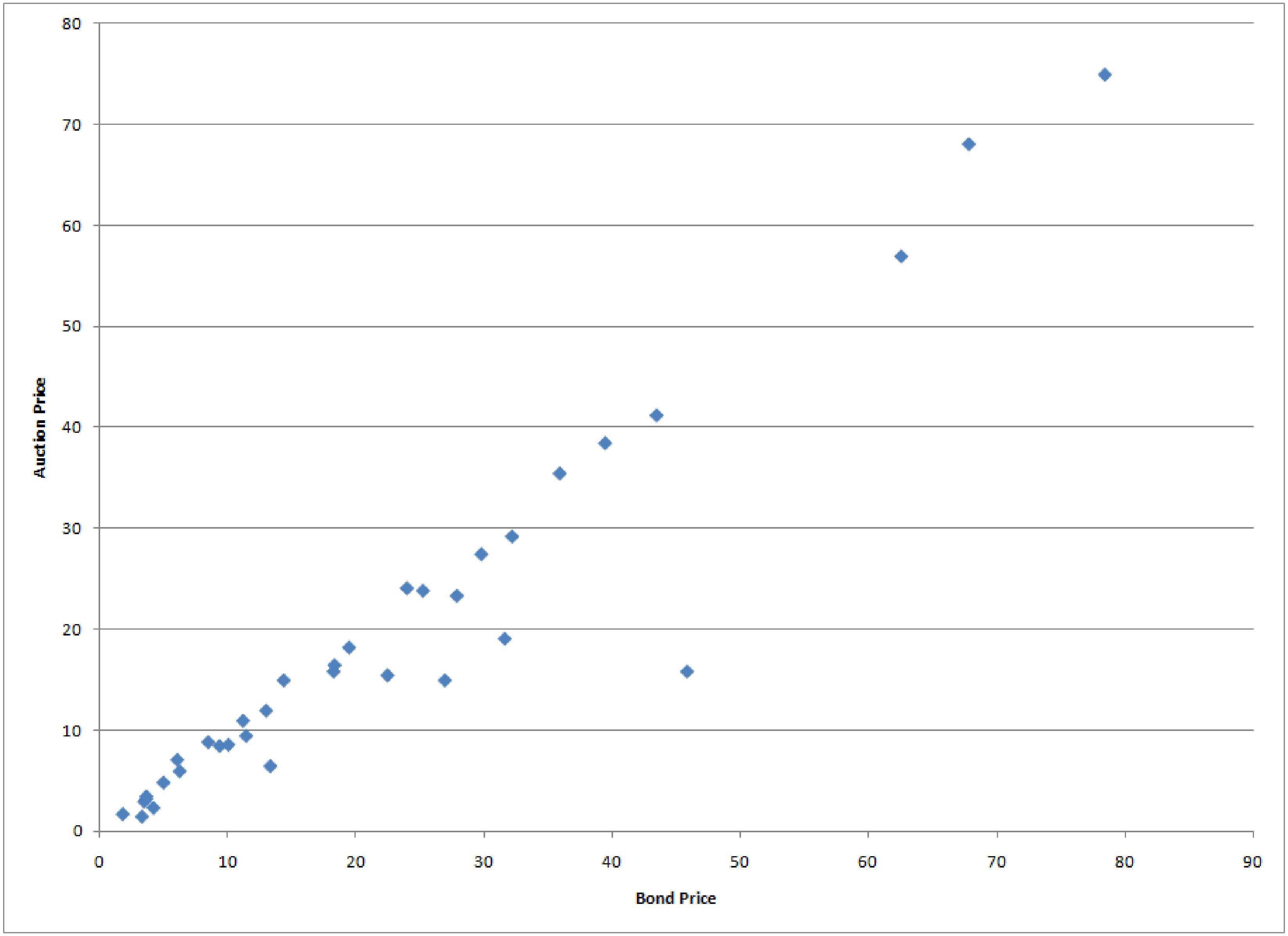


Figure 3: Scatter plot of bond price on auction day and auction price for BUY NOI auctions

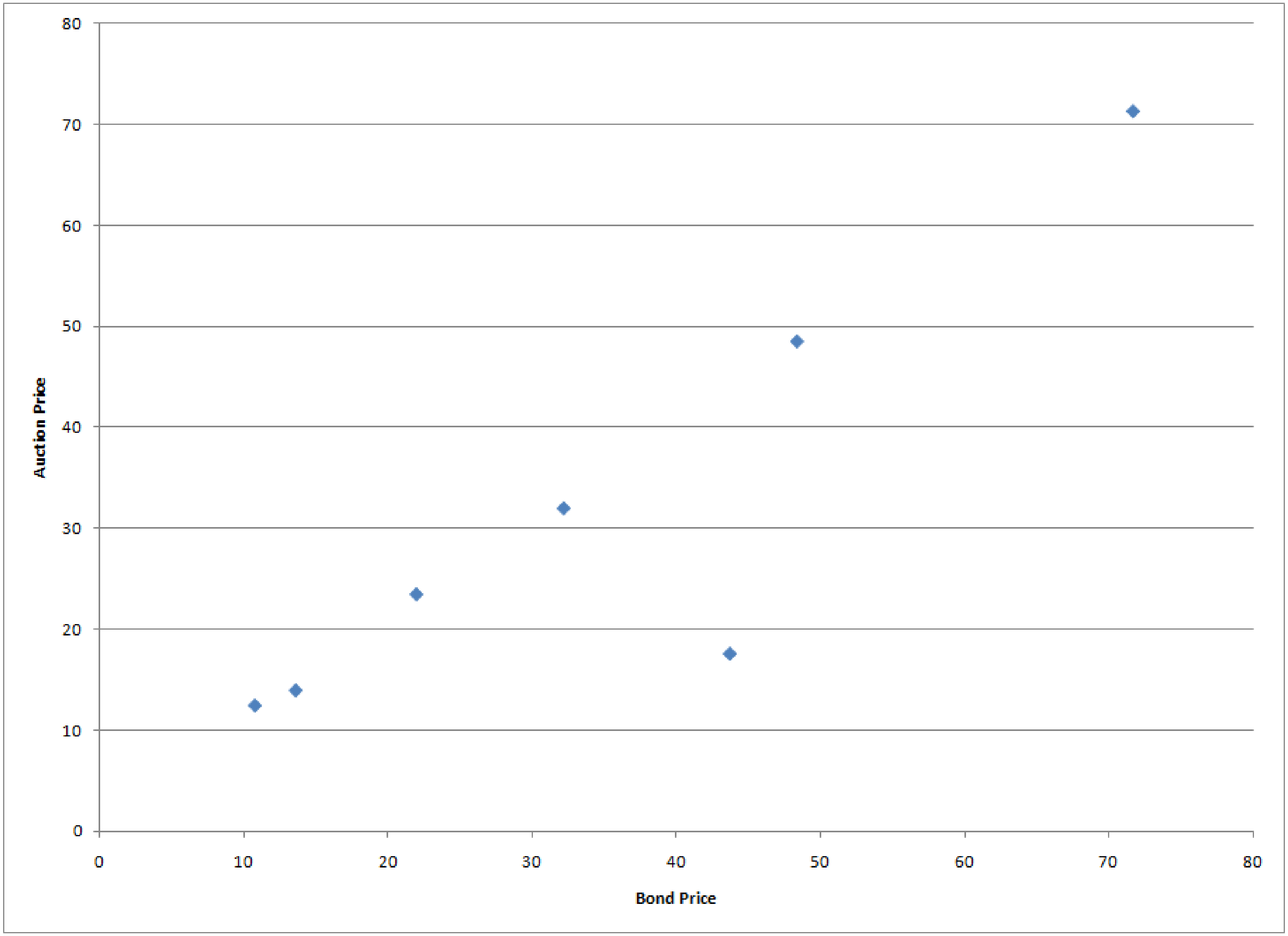


Figure 4: Bond price as a percentage of auction price in 5 days preceding and following auction day

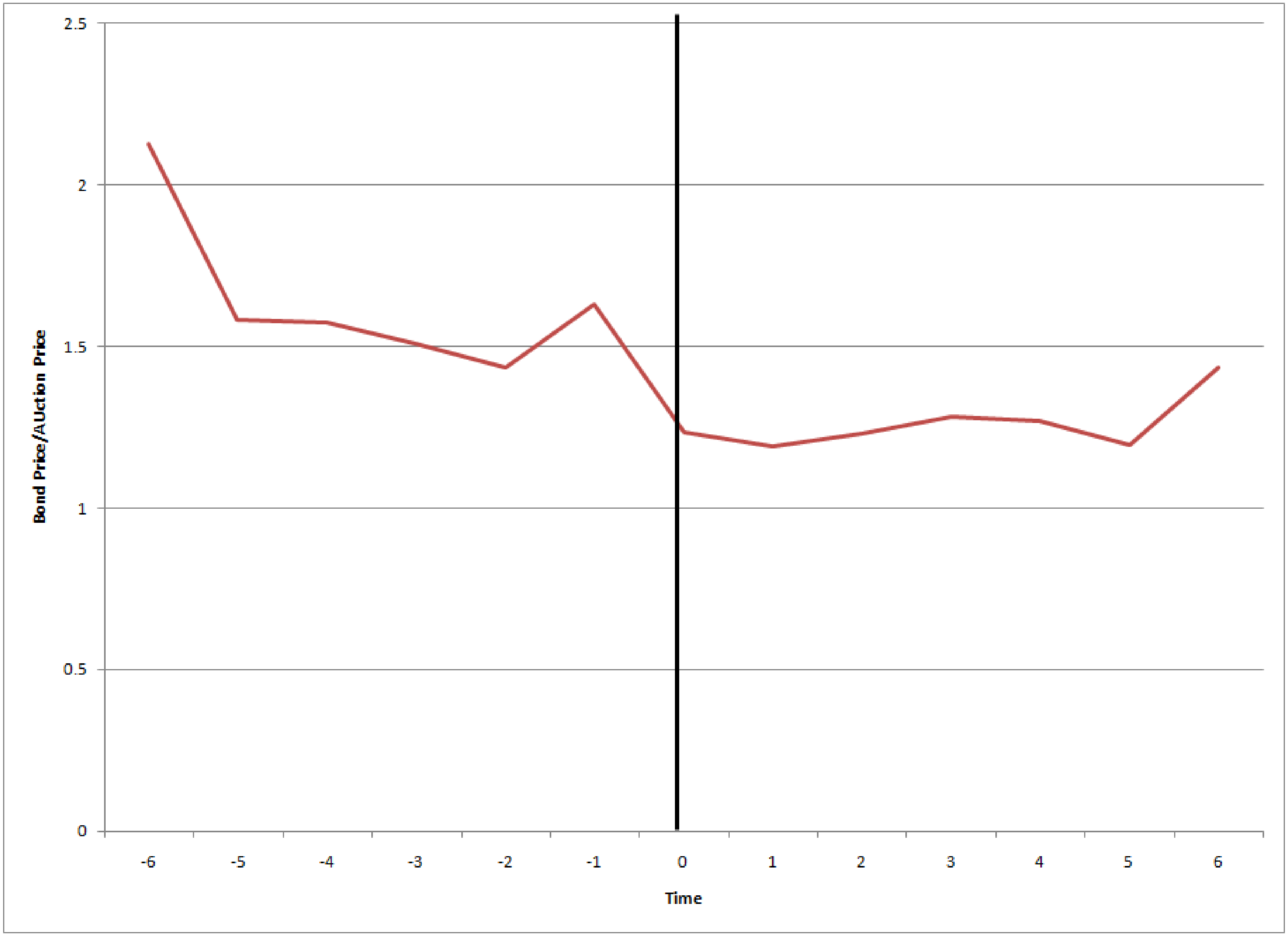


Figure 5: Bond price as a percentage of auction price in 10 days preceding and following auction day

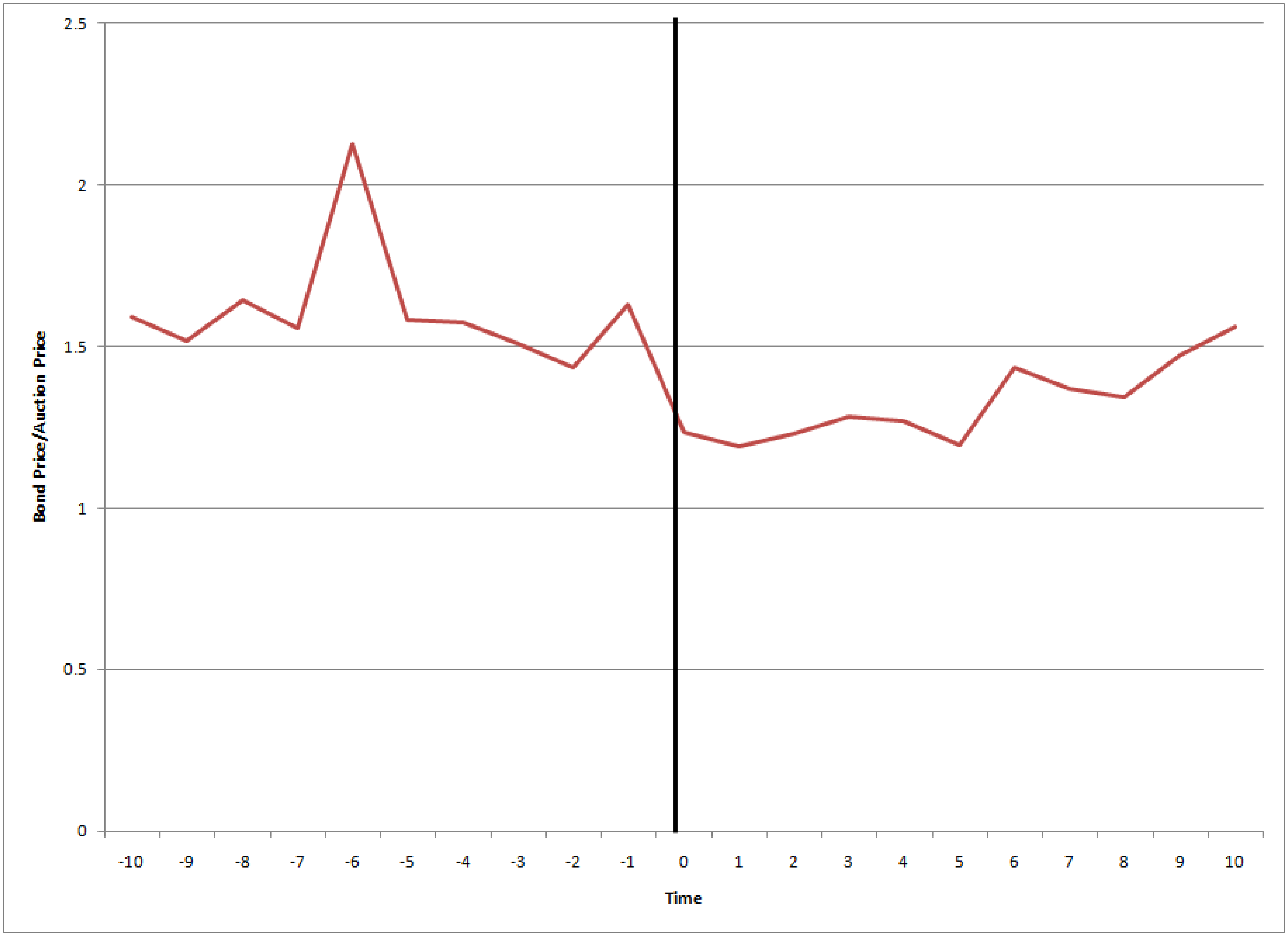


Figure 6: Bond price as a percentage of auction price in 15 days preceding and following auction day

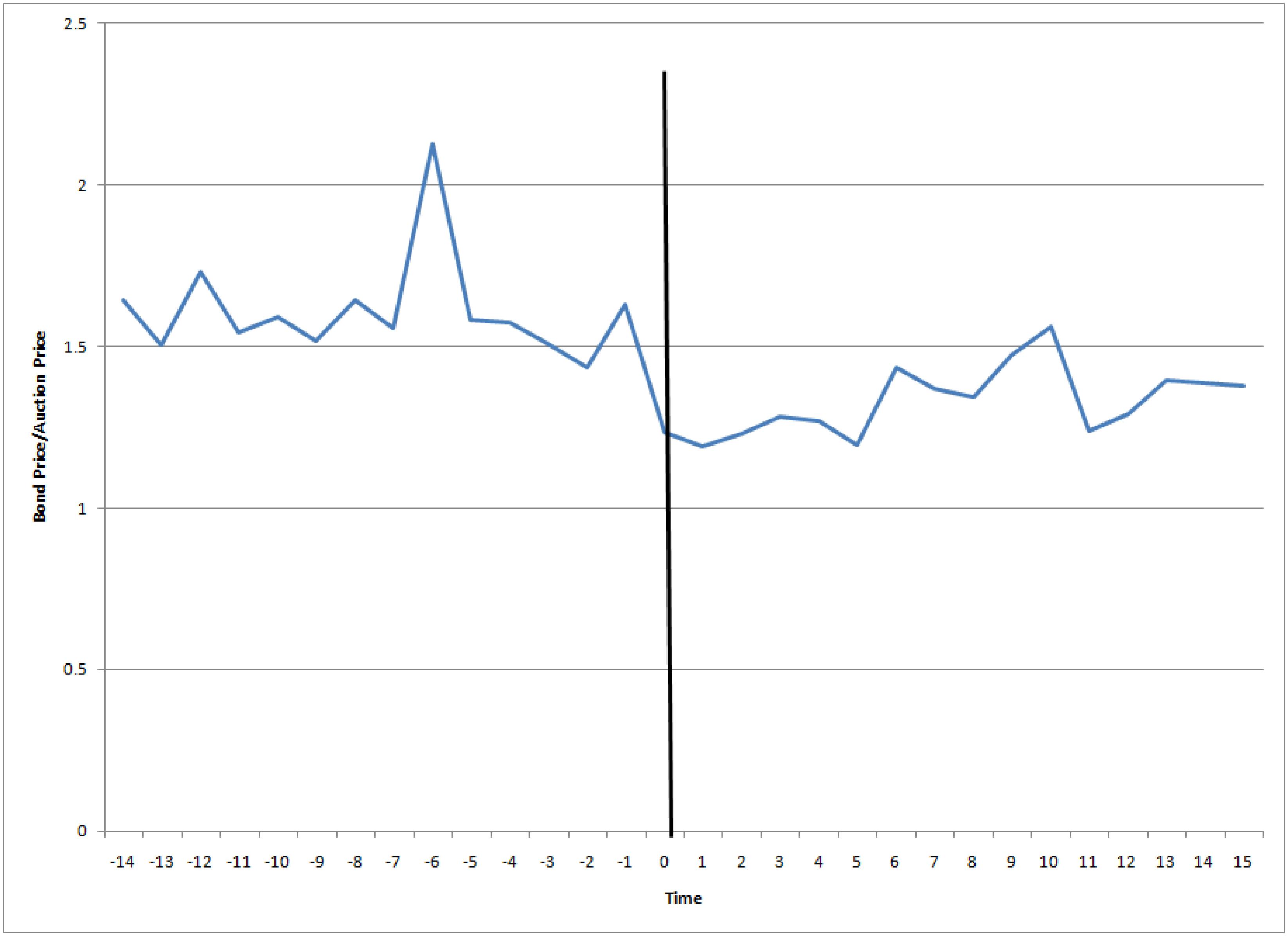


Figure 7: Distribution of Nominal Ultimate Recovery for BUY NOI Auctions

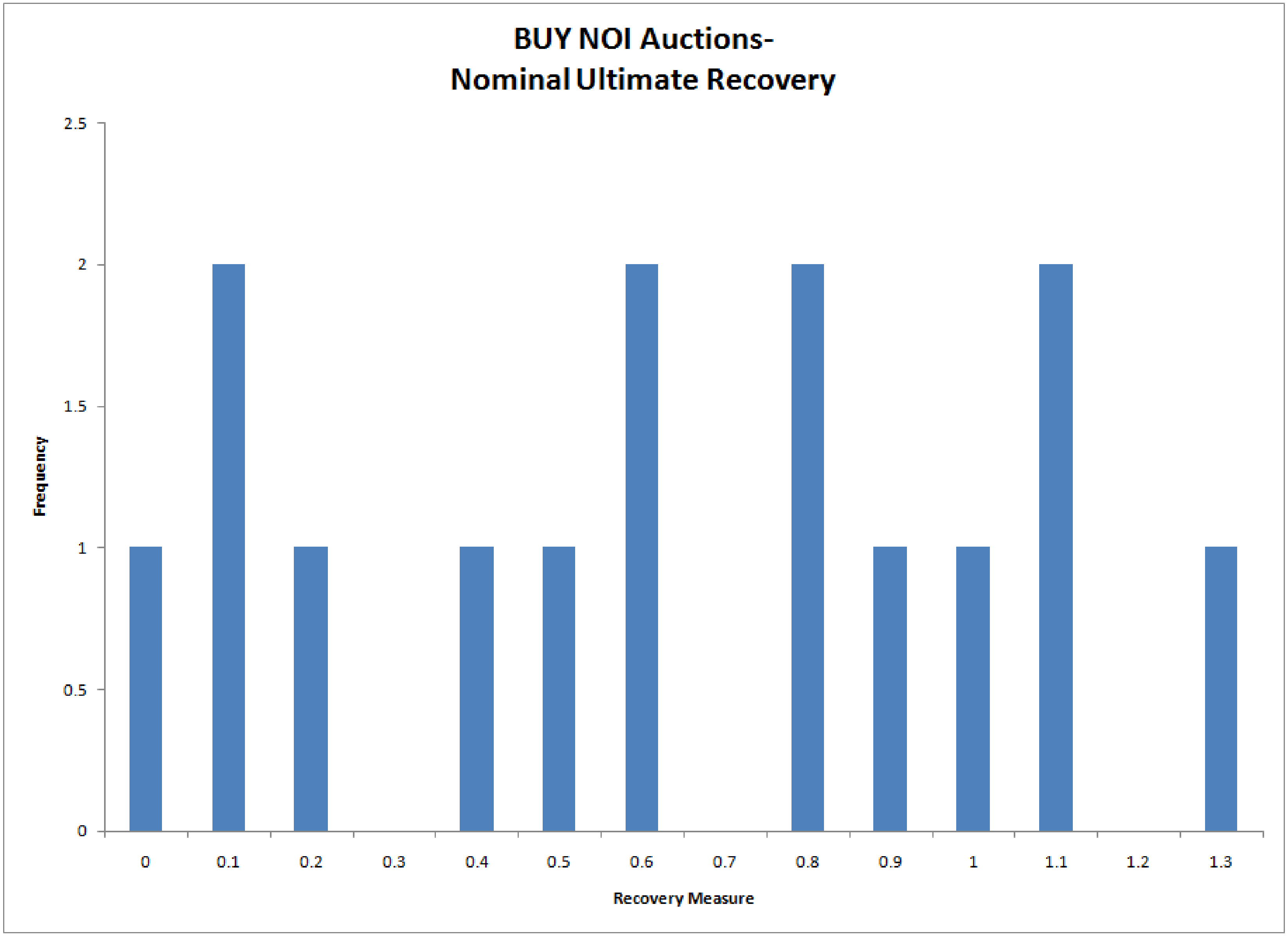


Figure 8: Distribution of Nominal Ultimate Recovery for SELL NOI Auctions

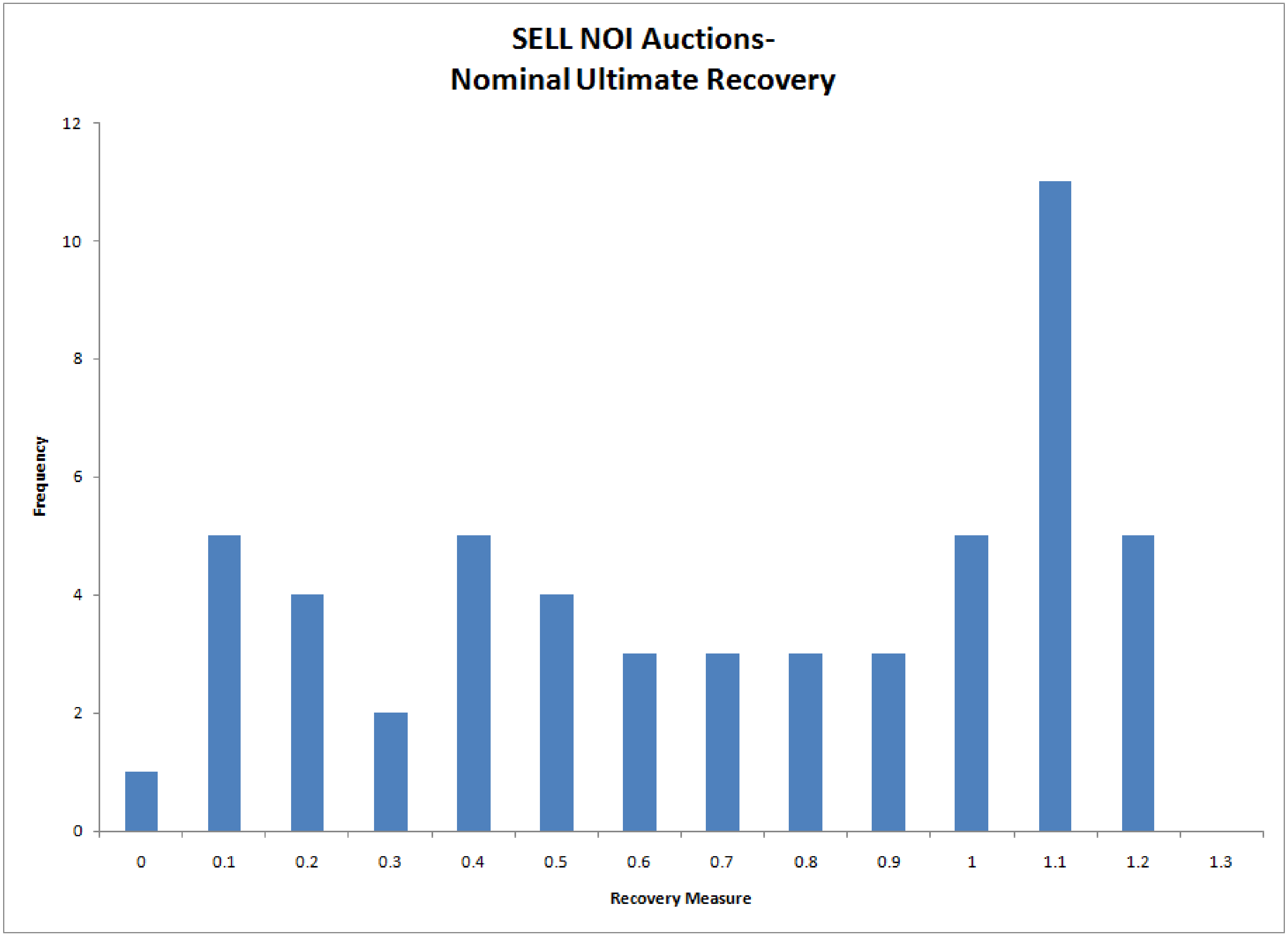


Figure 9: Distribution of Nominal Underrecovery for BUY NOI Auctions

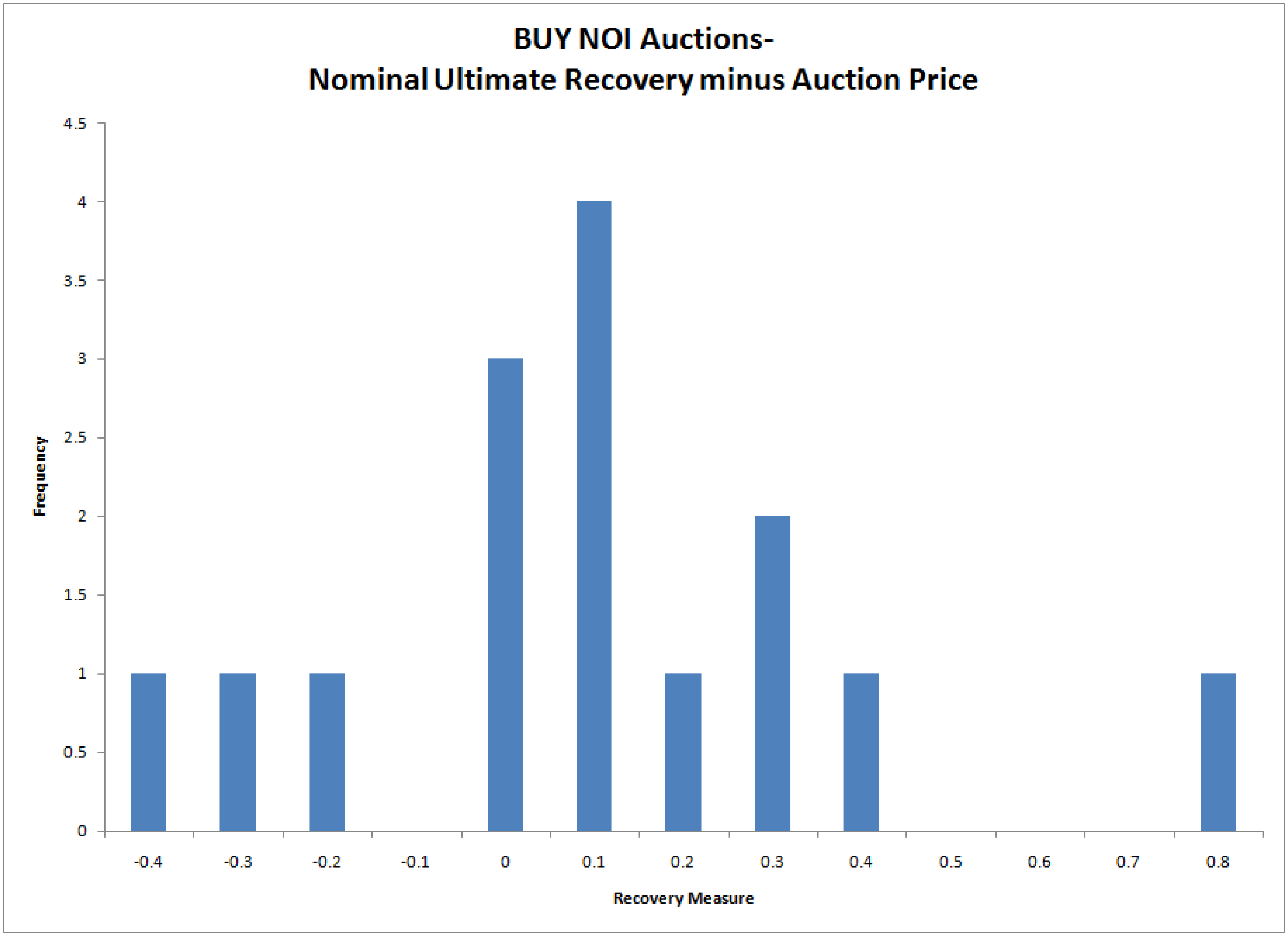


Figure 10: Distribution of Nominal Underrecovery for SELL NOI Auctions

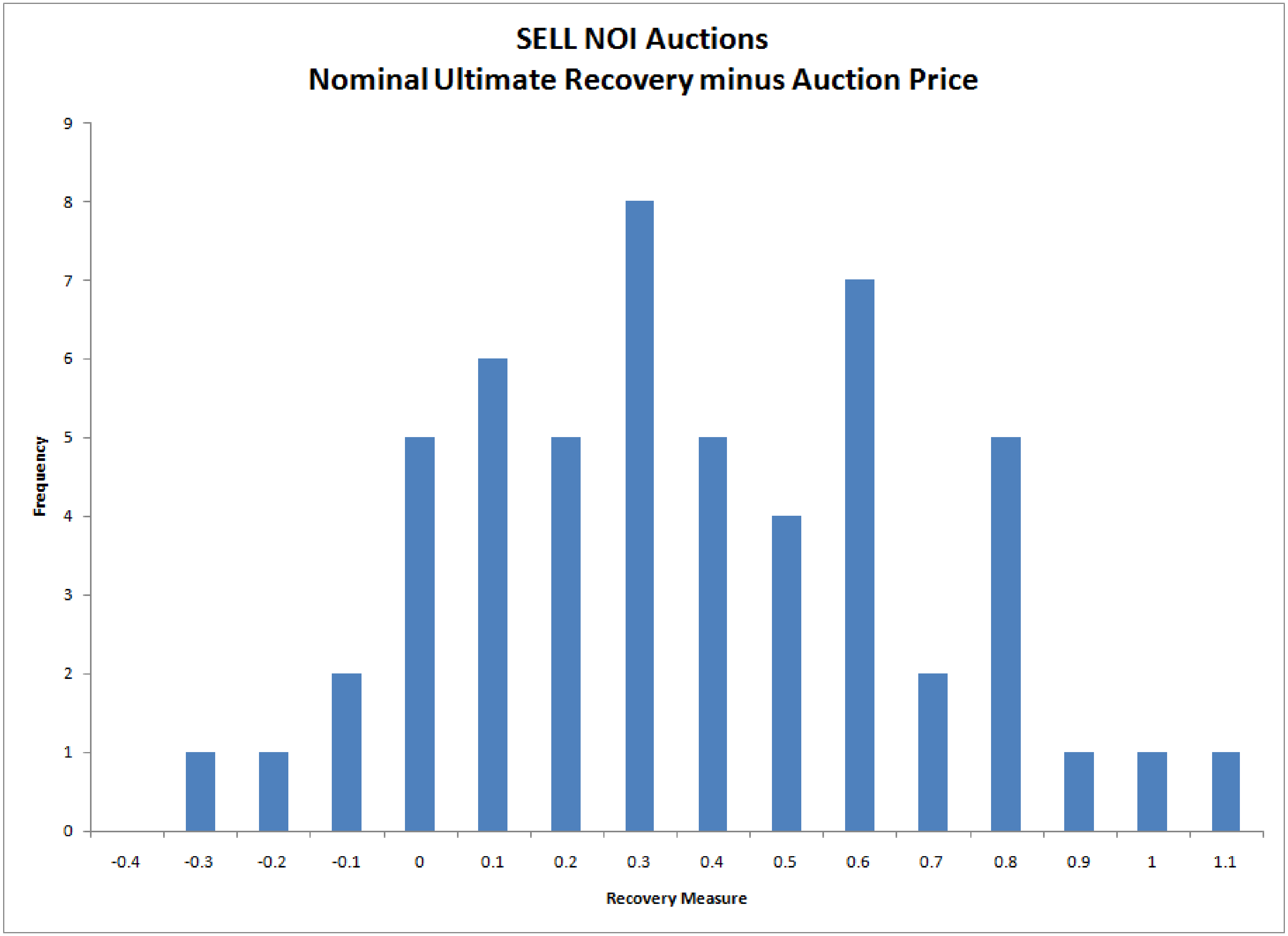


Figure 11: Distribution of Altman Adjusted Underrecovery for BUY NOI Auctions

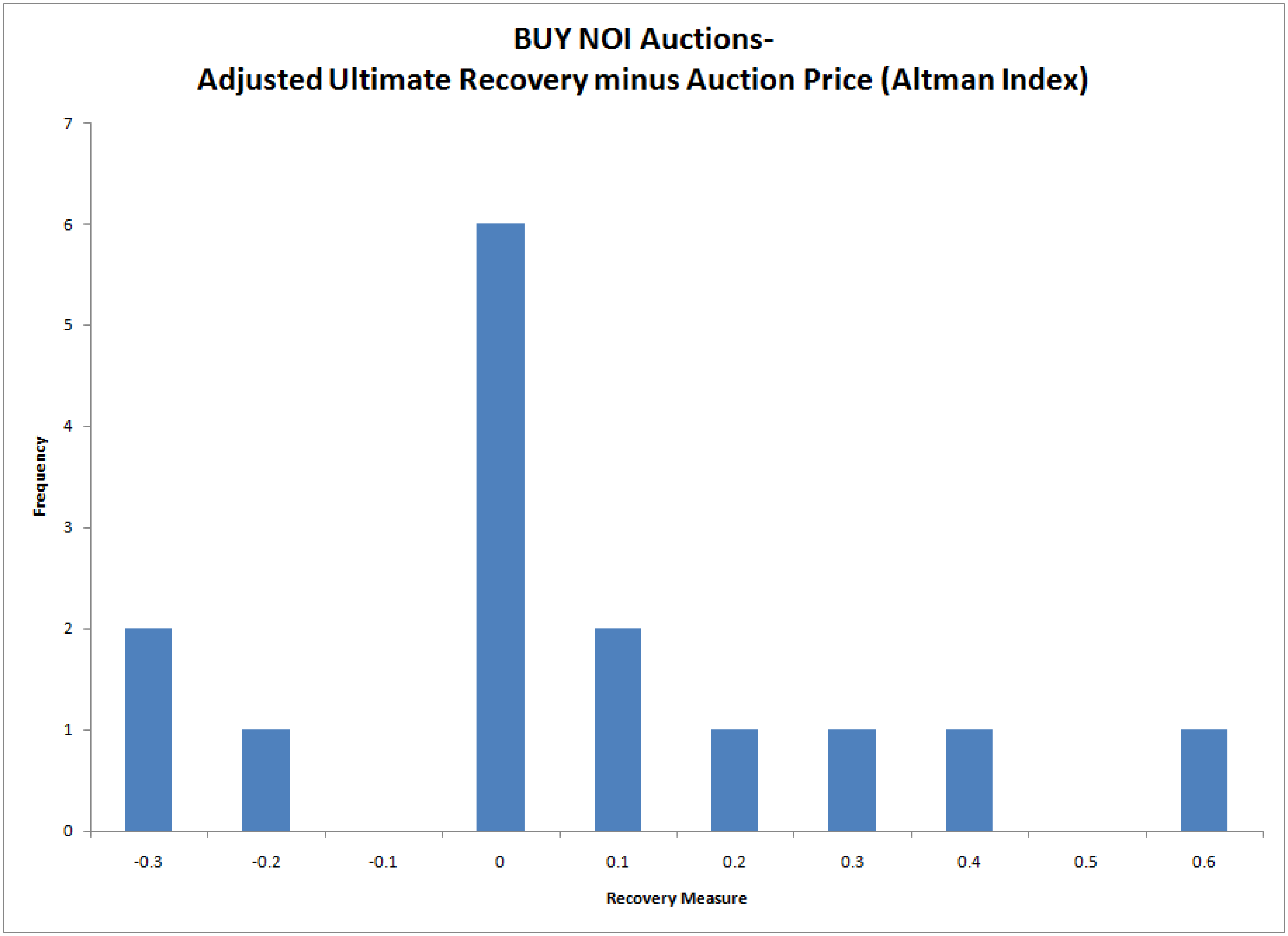


Figure 12: Distribution of Altman Adjusted Underrecovery for SELL NOI Auctions

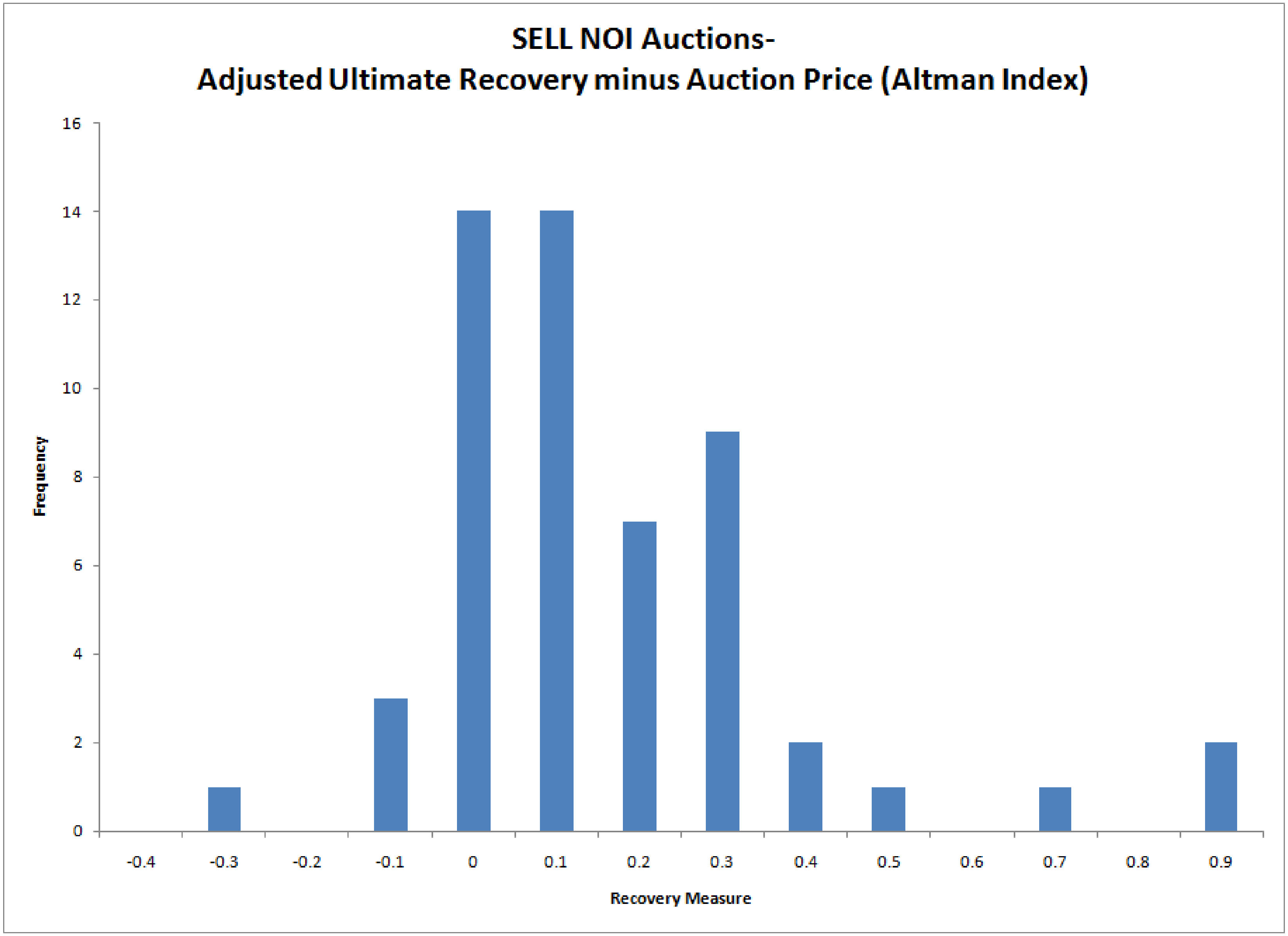


Figure 13: Distribution of High Yield Adjusted Underrecovery for BUY NOI Auctions

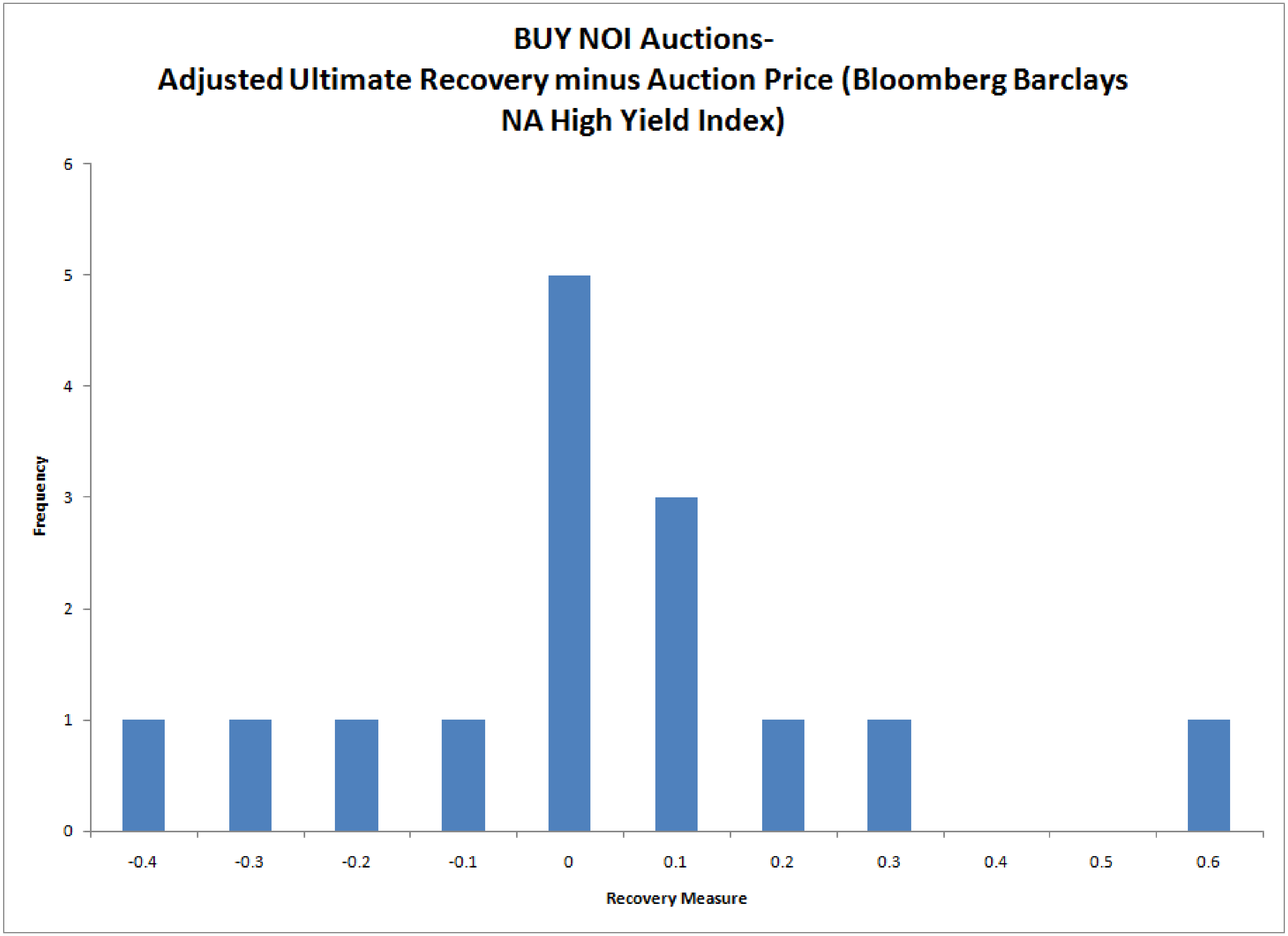
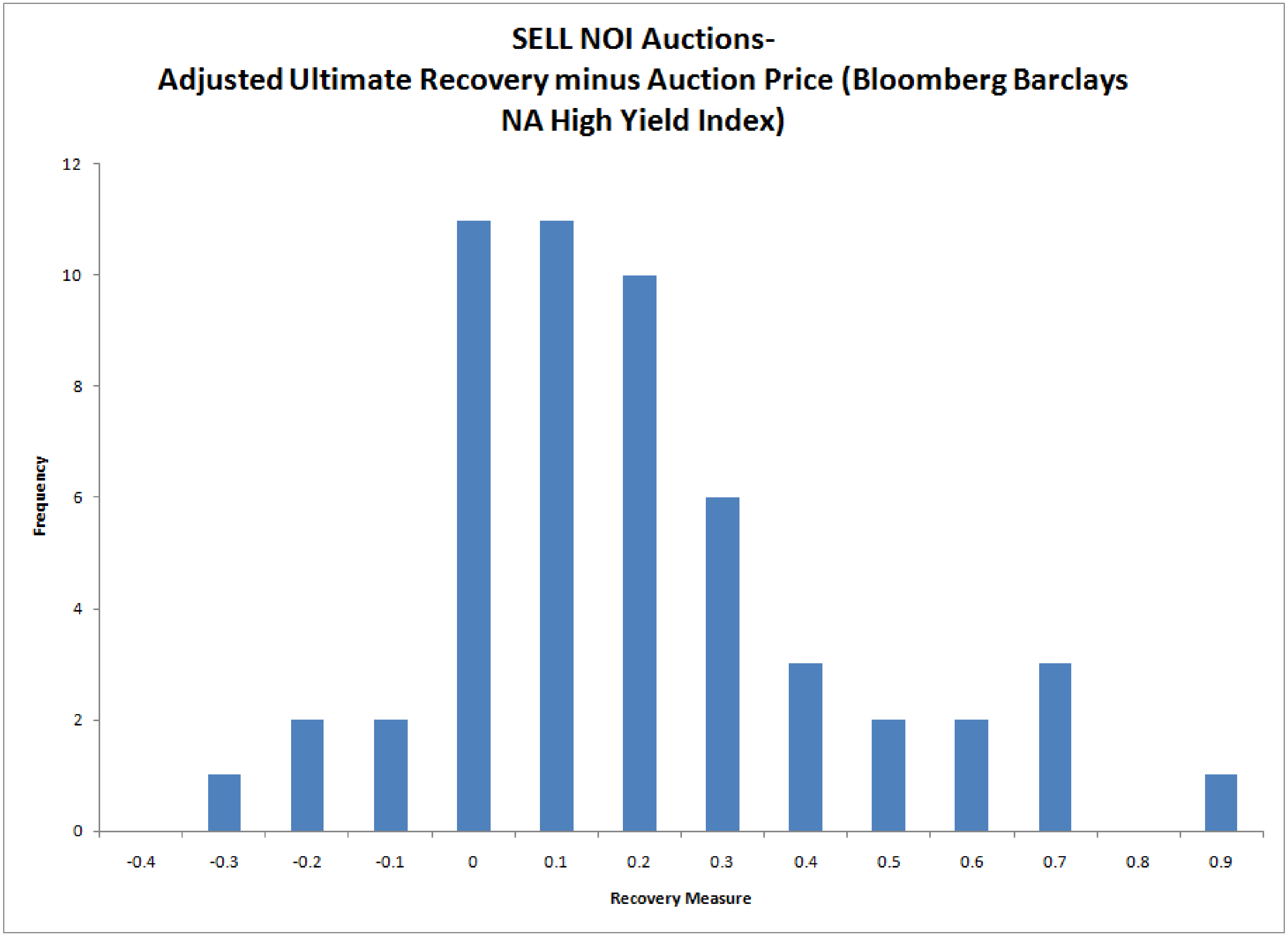


Figure 14: Distribution of High Yield Adjusted Underrecovery for SELL NOI Auctions



Appendices

A Measuring Recovery

The concept of recovery on credit securities that suffer from a credit event has at least two interpretations in the literature. These interpretations are based on the method used and the time at which recoveries are calculated. ultimate recovery (UR) requires usage of cash or cash value of securities at resolution of the credit event to calculate the recovery rate. Recovery-at-default (RaD) on the other hand uses prices of traded credit securities over a given interval of time in the post-default period to estimate recovery on those securities.

Models of credit risk measure RaD in three ways. These are Recovery-at-Face-Value (RFV), Recovery-at-Market-Value (RMV) and Recovery-of-Treasury (RT).

RFV assumes that the recovery amount bond holders receive (or the loss that they suffer) is best represented as a percentage of the par value of the bond on the default date. Thus under RFV if bond prices are a perfect estimate of the amount that bond holders will recover, a bond's recovery rate should be it's price divided by par value. This implies that issue-specific factors such as the time-to-maturity at the time of default, coupon and accrued interest at the time of default do not influence the recovery rate measure. An empirical implication of RFV is that prices of all issues of the same seniority should converge after default as issue-specific factors cease to matter.

RMV measures recovery as a percentage of the market price of the bond just prior to default. RT measures recovery as a fraction of the price of a risk-free treasury of the same coupon and maturity as the issue in default. Thus both RMV and RT allow issue specific factors such as time to maturity and coupon to influence the recovery-rate computation.

Guha (2003) relates these measures to the secondary market using a sample of 42 firms in default. He sources bond price data from Tradeline and these bonds range from zero to 27 years in maturity, across issues, at the time of default. He finds that after default or bankruptcy, bonds belonging to different issues of the same issuer trade within USD 2 of each other regardless of their issue-specific features. Given the small range of price differential between diverse issues post-default, he infers that bond markets measure recovery (or loss) as a percentage of the face value of the bond thereby validating the RFV method to measure recovery at default.

The measure used for RaD is critical to any analysis using bond prices to examine the efficiency of CDS auctions. This is because CDS auction prices are expressed as a percentage of the par amount outstanding at the date of default and all recoveries should be converted to RFV in order to make a comparison feasible. If RFV does not hold and there are issue-specific differences in bond prices, a recovery-rate measure based on average prices of bonds across issues may be biased for purposes of comparison with auction recovery.

Moreover, if a particular issue consistently trades below other eligible issues, a buyer of credit-protection can maximize her payout by opting for physical-settlement and delivering this issue. From her perspective, this issue would be cheapest to deliver (CTD). It is likely that most bonds delivered for settlement in the auction are CTD and thus auction-prices are most comparable to prices of CTD issues. Furthermore, "cheapness" of CTD issues may be related to the expected ultimate recoveries on them. Thus, the validity of RFV has an important bearing on the existence of a CTD issue and establishing a comparable benchmark for auction recoveries.

Following Guha (2003), I examine the implication of RFV for bankrupt firms in my sample using transaction level price and volume data from the Enhanced Trace database. Transaction level data allows me to perform the analysis with greater granularity. The sample period for each firm is 30 days after the filing of bankruptcy. I first extract high prices across issues for every firm for each day in the sample. I then compare the highest high price with the lowest high price for a firm, each day, across issues of the same seniority.

The difference between the two is plotted as a histogram in Figure 15. A Majority of observations lie outside the USD 2 range established by Guha (2003). The mean difference is USD 13.43 and significantly different from zero with 99 percent confidence. The median difference is USD 3.

Figure 16 is the histogram of the difference between the highest low price and the lowest low price across issues of the same firm for each day. Similar to Figure 9, a majority of observations lie outside the USD 2 range. The mean difference is USD 9.68 and significantly different from zero with 99 percent confidence. The median difference is USD 2.825.

Figure 17 is the histogram of the difference between the highest and lowest volume weighted prices across issues of the same firm for each day. Again, a majority of observations lie outside the USD 2 range. The mean difference is USD 10.57 and significantly different from zero with 99 percent confidence. The median difference is USD 2.5.

Given shallow trading in bond markets, the above results could be due to timing differences between trades in different issues. To minimize the impact of timing differences on these comparisons, I divide the trades in to non overlapping hourly intervals for each day. I then compute the volume weighted average price for each issue, for each firm, for each hourly interval, for each day. Figure 18 is the histogram of the difference between the highest and lowest volume weighted prices across issues, for each firm, for each day, for each hour. A large number of observations lie outside the USD 2 range. The mean difference is USD 7.82 and significantly different from zero with 99 percent confidence. The median difference is USD 1.85.

Thus, empirical implications of RFV don't hold in this sample and issue-specific differences are observed in prices of bonds of the same seniority after default. Persistent issue-specific differences can lead to a cheapest-to-deliver issue for the CDS auction.

B Ultimate Recovery and Recovery at Default

Previous studies use bond price based measures to examine CDS auctions while I use both ultimate recovery and secondary market data. In addition to issues associated with RFV and the difficulty in identifying the CTD issue ex-ante, several other factors contribute to the approach using UR.

Acharya, Bharath, and Srinivasan (2007) and Jankowitsch, Nagler, and Subrahmanyam (2014) argue in favor of using RaD on grounds that most holders of bonds are forced to liquidate their holdings on occurrence of a credit event due to institutional compulsions and therefore for these bondholders, RaD is the relevant recovery rate. However a CDS participant may not have a position in the underlying bonds. Oehmke and Zawadowski (2016) show that speculative activity is concentrated in CDS markets due to availability of standardized contracts of the same term, unlike in bond markets where a multitude of issues with different terms, coupons and liquidity make speculation difficult. Thus, these speculators are unlikely to have positions in underlying bonds and RaD may not be a relevant measure of recovery for them. UR is a direct measure of the loss on a credit security and a more relevant benchmark for CDS auction recoveries.

If bond prices in the post- default period are accurate estimates of UR then the choice between RaD and UR is redundant. Many studies have examined this question previously. Warner (1977) uses a sub-sample of railroad bonds (20 firms and 73 bonds) to form an equal weighted portfolio of bonds in default. He then compares its monthly performance to a risk-adjusted portfolio of stocks in non-bankrupt railroad firms over the same post-petition period. The bond portfolio generates statistically significant abnormal returns of 1.05 percent a month compared to its benchmark. Abnormal returns of the bond portfolio are concentrated in the 1940-1942 time period and do not hold when that time period is excluded.

Eberhart and Sweeney (1992) use a sample of 67 firms with 170 bonds to perform a series of tests examining market efficiency for bonds in default. They calculate actual returns of bonds in the post-default period to the month of emergence from bankruptcy. They posit that if the market is efficient, these returns should not be statistically abnormal when benchmarked against a model for bond returns. They further hypothesize that for market efficiency to be proven conclusively, these returns should yield an alpha of zero and beta of one when regressed on expected returns (derived from a model). They perform tests using both a model for bond returns and actual market returns as the benchmark. Tests based on the market model yield conflicting results while those using market returns support market efficiency. UR is not directly used for these tests and the bond price in the month of emergence from bankruptcy is considered to be an accurate estimate of UR.

Altman and Eberhart (1994) extend the study to 91 firms with 232 bonds but test for efficiency within each priority (seniority) category. They use bond price at default and UR on emergence to calculate returns on these bonds during the post-default period. They test for abnormality in these returns using the Blume-Keim low rated bond index as the benchmark. In a sample with several issues of the same underlying, their tests reject the hypothesis of bond price efficiency in the post-default period. Some sub-samples support efficiency for some classes of securities but not for subordinated securities which form the largest chunk of their sample. Therefore, while bond prices may be efficient in estimating UR for some sub-samples and for some time periods, this fact can not be generalized. Using UR for my analysis avoids these concerns about bond price efficiency in the post-default period.

Several studies have examined the presence of a liquidity component in bond prices and credit spreads[19]. If defaulted bond prices also have a significant liq-

[19] Huang and Huang (2012), Longstaff, Mithal, and Neis (2005), Ericsson and Renault

uidity component, measures of RaD may not be comparable recoveries in CDS auctions since CDS markets have standardized contracts that may be more liquid (Oehmke and Zawadowski (2016)). Moreover, if the liquidity component varies in magnitude due to issue-specific factors then this bias in RaD measures may not be uniform across auctions making RaD unsuitable for benchmarking auction recoveries.

Lastly RaD for LCDS auctions for loans requires high frequency loan pricing data post default. Due to the unavailability of this data most previous studies have ignored the sample of LCDS auctions. Using UR allows me to include LCDS auctions in the sample of this study.

C Theoretical Motivation

The efficacy of CDS auctions has been assessed theoretically by several researchers prominent among who are Chernov, Gorbenko, and Makarov (2013), Du and Zhu (2017) and Peivandi (2014).

Chernov, Gorbenko, and Makarov (2013) use the set up of Wilson (1979) and Back and Zender (1993) to analyze the auction theoretically. In their model agents are risk-neutral with identical valuations of the deliverable bonds. Agents' wealth comprises of four components. The first component is the value of their initial holding of bonds which is the product of the value of those bonds and the number of bonds that they hold. The second component is their payoff from the physical settlement in the auction which is the product of the number of CDS contract physically settled and the difference between the par value and the true value of the bonds. The third component is their payoff from the cash settlement in the auction which is product of the number of CDS contracts cash settled

(2006), Chen, Lesmond, and Wei (2007), Han and Zhou (2008), Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008), Das and Hanouna (2009), Rossi (2014), Chen, Fabozzi, and Sverdlove (2010), Bao, Pan, and Wang (2011), Feldhütter (2012), Helwege, Huang, and Wang (2014), Dick-Nielsen, Feldhütter, and Lando (2012), Friewald, Jankowitsch, and Subrahmanyam (2013).

(difference between the number of CDS contracts they hold and the number of CDS contracts that are physically settled) and the difference between the par value and the auction price. The last component is the product of the number of bonds allocated to the agent in the second stage of the auction and the difference between the value of those bonds and the auction price.

Thus the auction price affects only the third and fourth components of an agent's utility, that is the payoff from the allocation of bonds in the second stage of the auction and the part of the CDS position that is cash settled. No constraints are imposed on the aggregate quantity of bonds that the agents are endowed with, the number of contracts that are settled physically (requiring delivery of bonds) and the aggregate amount of bonds that are allocated to the agents through the second stage of the auction.

Short sale constraints (agents can only sell the amount of bonds they are endowed with) and holding constraints (some agents cannot hold bonds after the auction) are introduced in the model as trading frictions.

To solve the model without trading frictions, Chernov, Gorbenko, and Makarov (2013) first solve for the equilibrium outcome in the second stage of the auction for a given NOI and then solve for the optimal PSRs (physical settlement requests) submitted by the agents for the given equilibrium outcome in the second stage.

They show that in the absence of trading frictions a positive NOI can never be more than the net CDS positions of protection sellers and vice versa. Intuitively this can be understood through the following example. A positive NOI (or SELL NOI) is the difference between the SELL PSRs submitted by the protection buyers and the BUY PSRs submitted by protection sellers. Net CDS positions are defined as the difference between the total outstanding CDS contracts of an agent and the number of CDS contracts that are physically settled by the agent. In order to settle a contract physically, it is necessary to submit a PSR but a PSR does not always lead to a physical settlement. Only matched PSRs from the protection buyers and sellers are settled physically. Even if protection sellers were to settle zero contracts physically (by submitting zero PSR) and protection buyers were to try and settle all their contracts physically by submitting PSRs for their entire position, the NOI will be positive (SELL), at its maximum value and equal to the CDS positions of the protection buyers which is equal to the net CDS positions of the protection sellers (because they submitted zero PSRs). If any of the protection sellers were to submit a BUY PSR and/or any of the protection buyers submit a SELL PSR less than their entire CDS position, the NOI will be positive but less than the net CDS position of the protection sellers.

With a positive NOI which is less than the net CDS positions of the protection sellers (positions that will be cash settled based on the auction price), protection sellers have an incentive to bid up the price of the bonds above fair value in the second stage of the auction since the loss on purchasing the NOI amount of bonds will be more than offset by the gain from paying less on the cash settled contracts (which are larger in amount than the NOI). Thus a positive NOI (SELL) can lead to the auction price being higher than true value. Similarly a negative NOI (BUY) can lead the auction price to be lower than true value.

Chernov, Gorbenko, and Makarov (2013) show that in their model without trading frictions, irrespective of under or overpricing equilibrium, all agents can gain the same utility as they would if the auction price was equal to true value. This is because protection buyers and sellers can submit PSRs in the first stage of the auction so as to negate the impact of over or underpricing in the second stage of the auction. In the example considered previously, overpricing was an equilibrium outcome in the second stage of the auction (with a SELL NOI) as protection sellers bid up the price of the bonds above fair value to generate net gains from cash settlement at the cost of protection buyers cash settling their contracts. However protection buyers can ex ante negate the loss from the cash settled positions by submitting PSRs equal to their CDS positions in the first stage of the auction. This way the loss incurred by them on the cash settled contracts due to overpricing of bonds will be offset exactly by the gain from selling those bonds through the PSR and NOI. This holds symmetrically for situations where the NOI is BUY. Thus in a pure equilibrium there is no loss of utility to any of the agents.

These results are contingent on the assumption that there are no constraints on the supply of the bonds that can be used by the protection buyers for physical settlement. Given the issues with the settlement of CDS contracts of Delphi under old physical settlement regime, this assumption is open to question.

Chernov, Gorbenko, and Makarov (2013) introduce trading frictions in the form of short selling constraints. The model is solved under the assumption that each agent can only sell the amount of bonds that she is endowed with and that there exists at least one protection buyer whose CDS position is larger than her bond endowment. This constrains her from submitting SELL PSRs for her entire CDS position in the first stage of the auction. Under these conditions a sub game perfect overpricing equilibrium can be constructed where the auction price is 100 and protection sellers have utility far greater than what it would be if the auction price was equal to true value. Such equilibrium is possible because with at least one protection buyer unable to submit PSRs covering her entire CDS position, the NOI is smaller than the net CDS position of the protection sellers and they can bid up the prices for the NOI bonds with larger offsetting gains from their larger net CDS positions which are cash settled at a higher price.

If the second trading friction is imposed instead, the model predictions change significantly. The second friction assumes that there exists at least one protection seller who cannot hold a positive amount of bonds after the auction. This friction is intended to capture the presence of pension funds and/or insurance companies who cannot hold bonds of firms in default. Under this assumption an equilibrium can be constructed where the final auction price is a decreasing function of the NOI. If the protection buyers have very large CDS positions, they have an incentive to submit large SELL PSRs so as to generate a positive NOI

(SELL) at the end of the first stage of the auction. Since the final auction price is a decreasing function of the NOI, a large SELL NOI will lead to a price lower than true value. The loss incurred by the protection buyers by selling bonds at less than true value in the second stage of the auction will be more than offset by the gains from their larger cash settled positions (at less than true value of recovery). Since protection seller(s) are constrained from holding bonds after the auction they will be unable to correct the underpricing by purchasing bonds in the second stage.

Thus under Chernov, Gorbenko, and Makarov (2013) when protection buyers are constrained from submitting PSRs for their entire CDS position, protection sellers can bid up prices in the second stage of the auction to generate gains in their cash settled positions thereby leading to overpricing. Conversely, when protection sellers are constrained from holding bonds after the second stage of the auction, protection buyers can submit higher PSRs to create a large NOI which can lead to underpricing of their bonds but generates greater than offsetting gains on their cash settled CDS positions.

The empirical implications of Chernov, Gorbenko, and Makarov (2013) are that both under and overpricing are possible with a SELL NOI and vice versa. For underpricing to be correlated with a SELL NOI, there must be an inverse relationship between the size of the NOI (SELL) and the final auction price. These implications are the primary motivation for my study.

Du and Zhu (2017) examine the efficiency of the CDS auctions in the context of the participation constraints imposed by the current format. Under the current rules, only protection buyers can submit SELL PSRs (to the extent of their CDS position) and only protection sellers can submit BUY PSRs. In the second stage, only bids are allowed if the NOI is SELL and vice versa.

Du and Zhu (2017) construct a two period model where the initial CDS and bond positions are endogenously determined by a quadratic cost function. In the next time period, the bond defaults with a given probability. Upon default, either a high state or a low state is realized with equal ex ante probability. In the high state more than fifty percent of the agents have a high value for holding the bonds while the remaining have a low value for holding them and vice versa in the low state. These values are independent of the value that accrues to each agent from her CDS position. This feature of the model is intended to capture the differential value placed on the same bond by various agents depending on their ability to manage and profit from the restructuring or bankruptcy process of the defaulted bond.

Thus the utility of an agent comprises of the time zero benefit of the CDS position, the time zero cost of the CDS position, the time zero CDS inventory cost, the time one payout from CDS settlement, the time one profit from the bonds traded in the CDS auction and the time one inventory cost of the bond position traded in the CDS auction. As in Chernov, Gorbenko, and Makarov (2013), no constraints between the supply of bonds and the number of bonds traded in the auction are modeled. The trading of bonds after default but before the auction is not modeled as the authors consider such trading to be more costly than trading the bonds in the auction.

Du and Zhu (2017) then establish a competitive benchmark for the CDS auction through a double auction where each agent is allowed to submit an unconstrained demand schedule, unlike in CDS auctions. They then analyze the efficiency of the outcomes of the two stage CDS auction with respect to the outcomes of the above benchmark. In the model, a trader with a high value for the bonds may not have an underlying CDS position or may be a protection buyer. This constrains her from participating in the first stage of the auction with a BUY PSR despite having a high value for the bonds. Some low value traders are similarly constrained in the first stage of the auction. In the second stage of the auction, participation constraints are imposed by the direction of the NOI. If the NOI is SELL, low value traders are unable to participate as they have a low value for the bonds and would like to sell but only buy orders are allowed. Similarly if the NOI is BUY, high value traders are constrained from participating in the second stage of the auction as they want to buy but only SELL orders are allowed.

Thus in the high state, while the NOI is BUY, only sell orders are allowed which means that low value traders dominate the second stage of the auction (as high value traders are unable to participate) leading to a price which is lower than the competitive benchmark (double auction) where the demand schedules for both low and high value traders are unconstrained. Similarly, the low state leads to a SELL NOI where only buy orders are allowed and high value traders dominate, leading to a price which is higher than the one established by the competitive benchmark.

Empirical examination of the model requires detailed information on bond positions, CDS positions and quotes submitted by each of the participating dealers, pre and post auction. Some predictions of the model can be tested under certain assumptions. The model predicts underrecovery for SELL NOI auctions and vice versa in comparison to theoretical outcomes of a double auctions which the authors consider to be efficient. Assuming that the efficient outcomes of the double auction are likely to be same as the true recovery values, allows for the underpricing/overpricing predictions to be tested in my sample. These predictions are opposite to those of Chernov, Gorbenko, and Makarov (2013).

Lastly, Peivandi (2014), examines CDS auctions as a mechanism design problem. He models the participation choices of agents and shows that no auction format is robust to bilateral or parallel settlement among some agents leading to incomplete participation in the CDS auction and biased prices. Only a posted price mechanism where the CDS contracts are settled at a price equal to the expected value of the bond, conditional on the information available to the mechanism designer is robust to participation choices of the agents and produces and unbiased price. Given the lack of detailed data on participation of agents in the CDS auction, I do not evaluate Peivandi (2014)'s predictions empirically.

D Estimating Certainty Equivalents

The estimation of certainty equivalents requires information on the distribution of ultimate recoveries and its key moments. In the absence of much information about the distribution of ultimate recoveries, I use an approach based on the conditional distribution of ultimate recovery. Given limitations of data, my approach differs for the loan and bond samples.

For all the bonds in my sample I first estimate daily volume weighted prices as outlined by Bessembinder, Kahle, Maxwell, and Xu (2008) from the cleaned Enhanced TRACE database. Then, I average these prices over the interval of time between declaration of bankruptcy or credit event and the CDS auction. Issues with the liquidity of the bonds in default manifest themselves in this exercise and I lose 2 observations out of 44 on account of no trade in those bonds after default. Using a different interval which more closely straddles the auction dates leads to the loss of even more observations and therefore I perform the analysis with bond prices averaged over the entire time interval between the credit event and the auction. I assume that this price imputes most of the information relevant for the estimation of the ultimate recovery rates ex ante. I then regress the ultimate recoveries on these bond prices and use the coefficients of the bond price (which are significant) to estimate the mean of the distribution of ultimate recoveries for each firm. I assume that ultimate recoveries of all firms have the same Gaussian distribution and identical variance which is estimated as the variance of the residual in sample. These assumptions yield the Gaussian distributions of ultimate recovery for each credit event. The mean of each of these distributions is different but the variance is same.

I then draw ten thousand observations from these distributions and estimate the utilities associated with each of them using a CRRA utility function with a coefficient of risk aversion of 2. I ascertain the mean utility and back out the certainty equivalent. I repeat this exercise ten thousand times and take the mean of the ten thousand certainty equivalent estimates as my measure of the certainty equivalent. I discount them at the risk free rate obtained from OIS Swaps for the time period between auction date and date of ultimate recovery. I do this for each firm in the sample Lastly, I regress the certainty equivalent estimates on auction-prices and an indicator for Sell-NOI.

Results in column A of Table 11 show that coefficient for the NOI indicator is not significant thereby implying that the conditional on pre-auction information embedded in bond prices the certainty equivalent estimates do not differ significantly from the auction outcome on account of the NOI.

However given the small size of the sample, individual but extreme observations can have a large effect on the significance of estimates. In order to verify the robustness of these inconclusive results, I apply the same econometric specifications on a winsorized version of the sample. Specifically I remove one observation each of certainty equivalents which are farthest from the auction price on both positive and negative sides, that is, I remove the observation which represents greatest underrecovery and also the observation which represents the greatest overrecovery.

As can be seen in column B of Table 11 the results from the winsorised sample show that certainty equivalents are significantly higher than the auction outcomes for Sell-NOI auctions. These results are in line with the main findings of the study and conform to theoretical predictions about the auction process.

Due to the unavailability of loan prices I use an alternative but less robust approach. Khieu, Mullineaux, and Yi (2012) show that ultimate recoveries for loans depend on firm specific, industry and economic factors. Their results imply that the most significant determinants of loan recovery rates are the nature of collateral, firm indebtedness at the time of bankruptcy, industry performance prior to bankruptcy, prior year GDP and time to emerge from bankruptcy. I use the coefficients from their analysis to estimate the mean of the recovery distributions for each of the firms in my sample. I then compare these estimates to the actual recoveries in my sample and compute the sum of squared errors which allows me to estimate the variance of the residuals. Similar to the analysis of bonds I assume that these distributions are Gaussian. I then apply the same methodology as I did for bonds to estimate the certainty equivalents for loans in my sample. This approach is much weaker compared to the one adopted for bonds.

Column C of Table 11 outlines the regression results for the loan sample. The certainty equivalents are not higher than the auction price for auctions where the NOI is “Sell”.

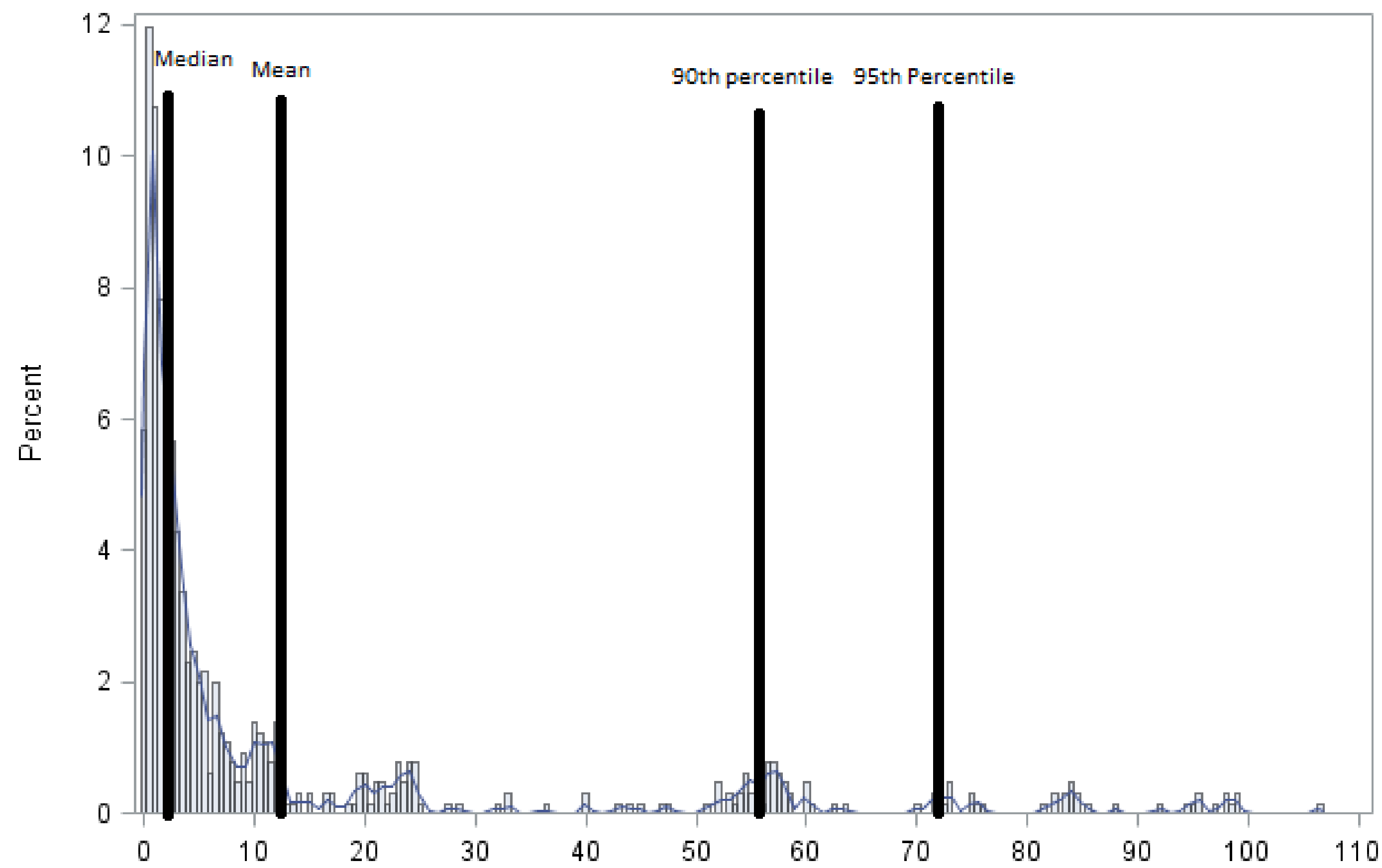
Given the limitations of data and restrictive assumptions involved the estimation of certainty equivalents, these results are inconclusive in establishing efficiency of CDS auctions and at best marginally support Chernov, Gorbenko, and Makarov (2013) predictions of underrecovery.

Table 18: OLS Regressions for certainty equivalents of ultimate recoveries

OLS regressions of certainty equivalents of bond and loan ultimate recoveries on the auction price and a binary variable which takes the value of one if the auction has a SELL-NOI and 0 otherwise. Column A includes the full sample of bonds auctions, column B includes a winsorised sample of bonds auctions and column C pertains to the sub sample of loan auctions. T Statistics are in parentheses.			
	A	B	C
Intercept	.08747 (2.48)**	.0089 (0.41)	(.0927) (5.49)***
SELLDUMMY	(.0256) (.79)	.04387 (2.25)**	.0032 (.28)
Auction Price	.6222 (9.65)***	.6722 (17.14)***	.0442 (2.23)**
Adjusted R Squared	0.71	0.89	0.12
Observations	42	40	24
*, ** and *** represent significance at 90%, 95% and 99% confidence respectively.			

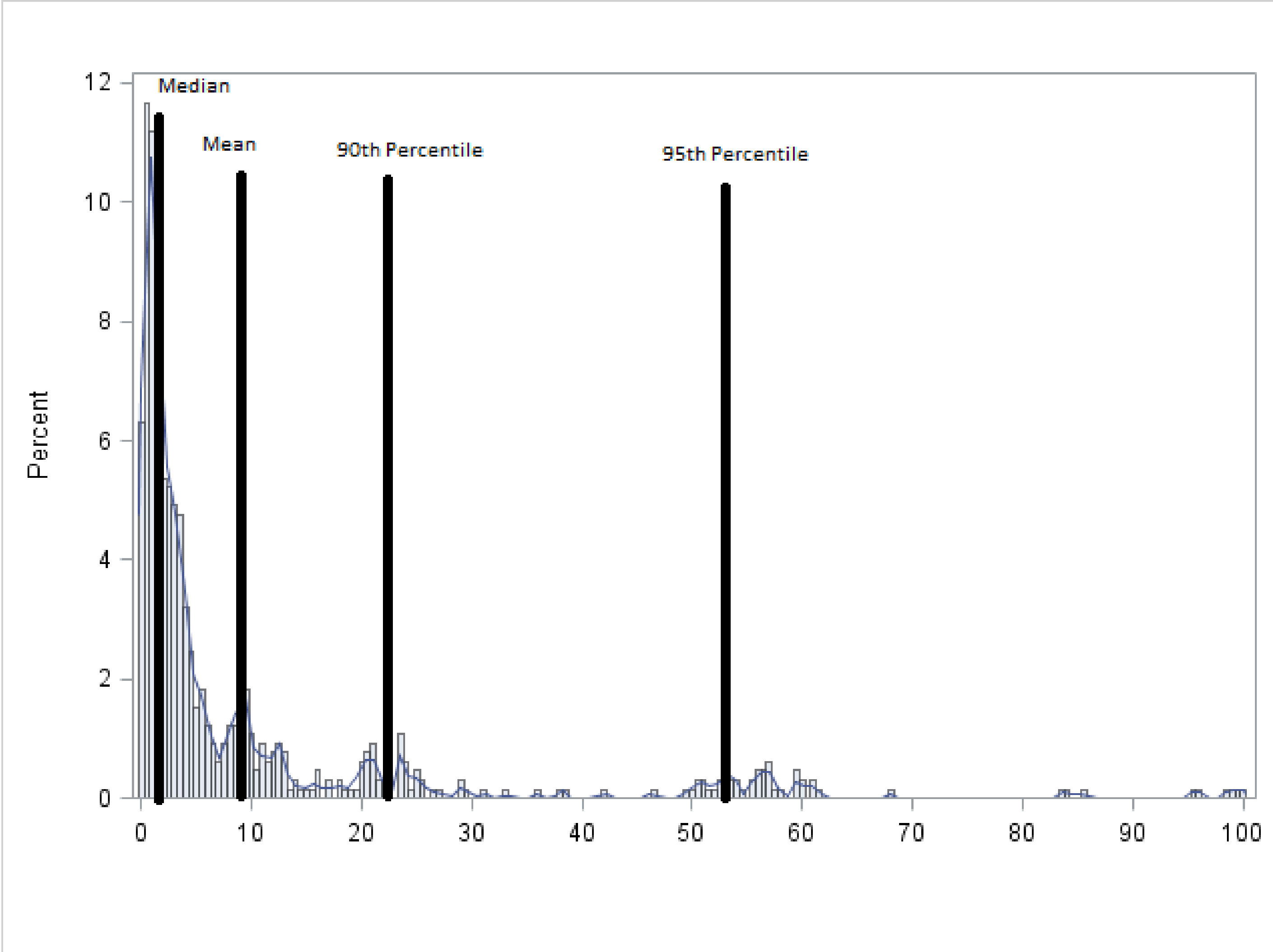
Note:Certainty equivalents for CDS auctions are estimated by regressing ultimate recoveries on average pre-auction bond prices and using the coefficients to calculate the mean of of the conditional distribution of ultimate recoveries for each auction. distribution is assumed to be Gaussian with equal variance for all auctions. The variance is estimated as the variance of the residual. CRRA utility function with a coefficient of risk aversion of 2 is used to calculate the utility of ten thousand draws of ultimate recovery and the certainty equivalent is backed out. This exercise repeated ten thousand times for each auction to get an average certainty equivalent. For LCDS auctions, coefficients of determinants of loan ultimate recovery are not estimated but taken from Khieu, Mullineaux, and Yi (2012).

Figure 15: Distribution of differences in high prices across issues for each firm day



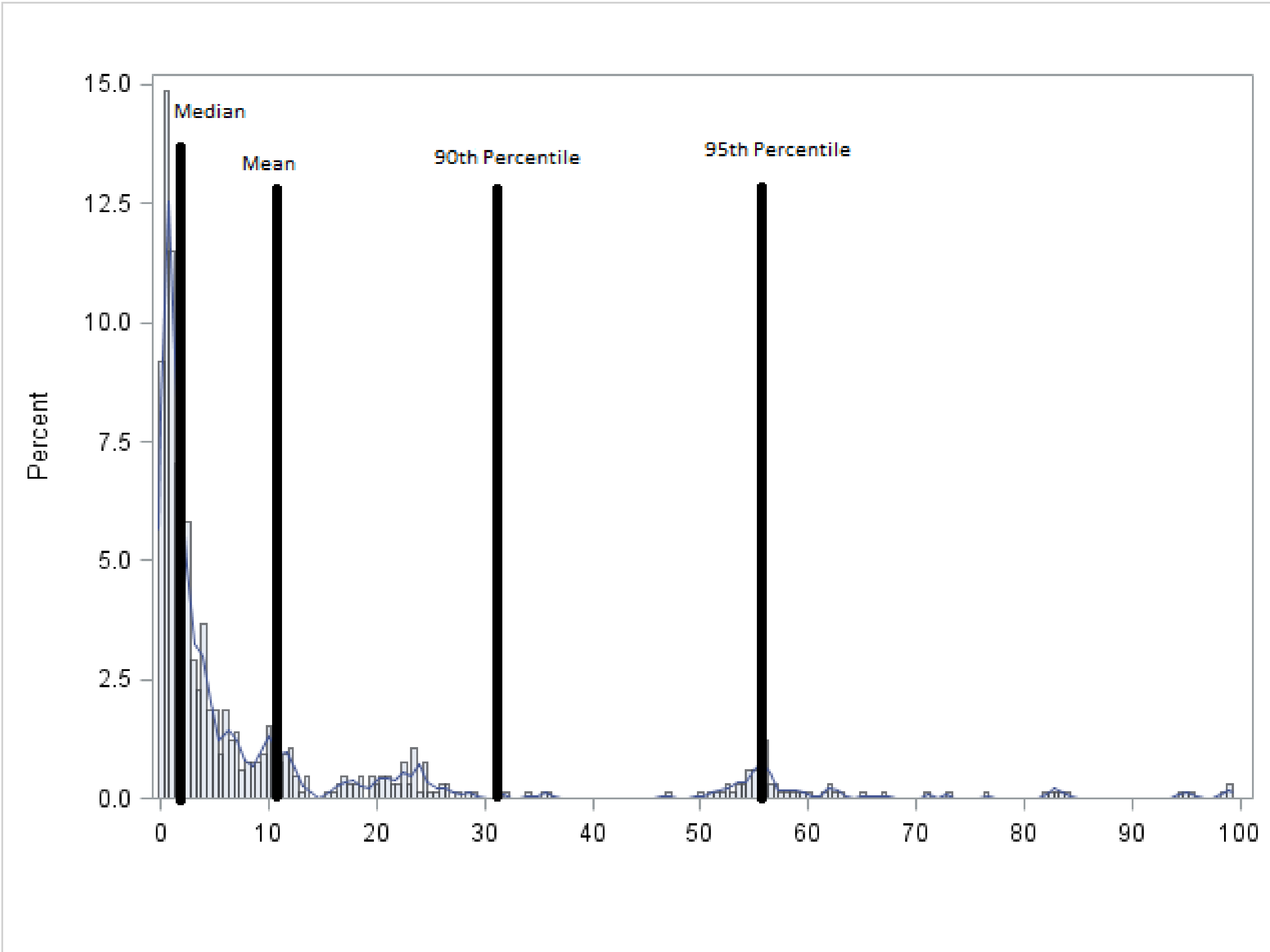
Distribution of differences between the highest high price and the lowest high price across issues of the same firm for each day after bankruptcy. Bin size for histogram is 0.5. Percent of observations in a bin are on the X-axis. Sample is restricted to 30 days after bankruptcy. The solid line is a kernel density function with bandwidth of 0.1.

Figure 16: Distribution of differences in low prices across issues for each firm day



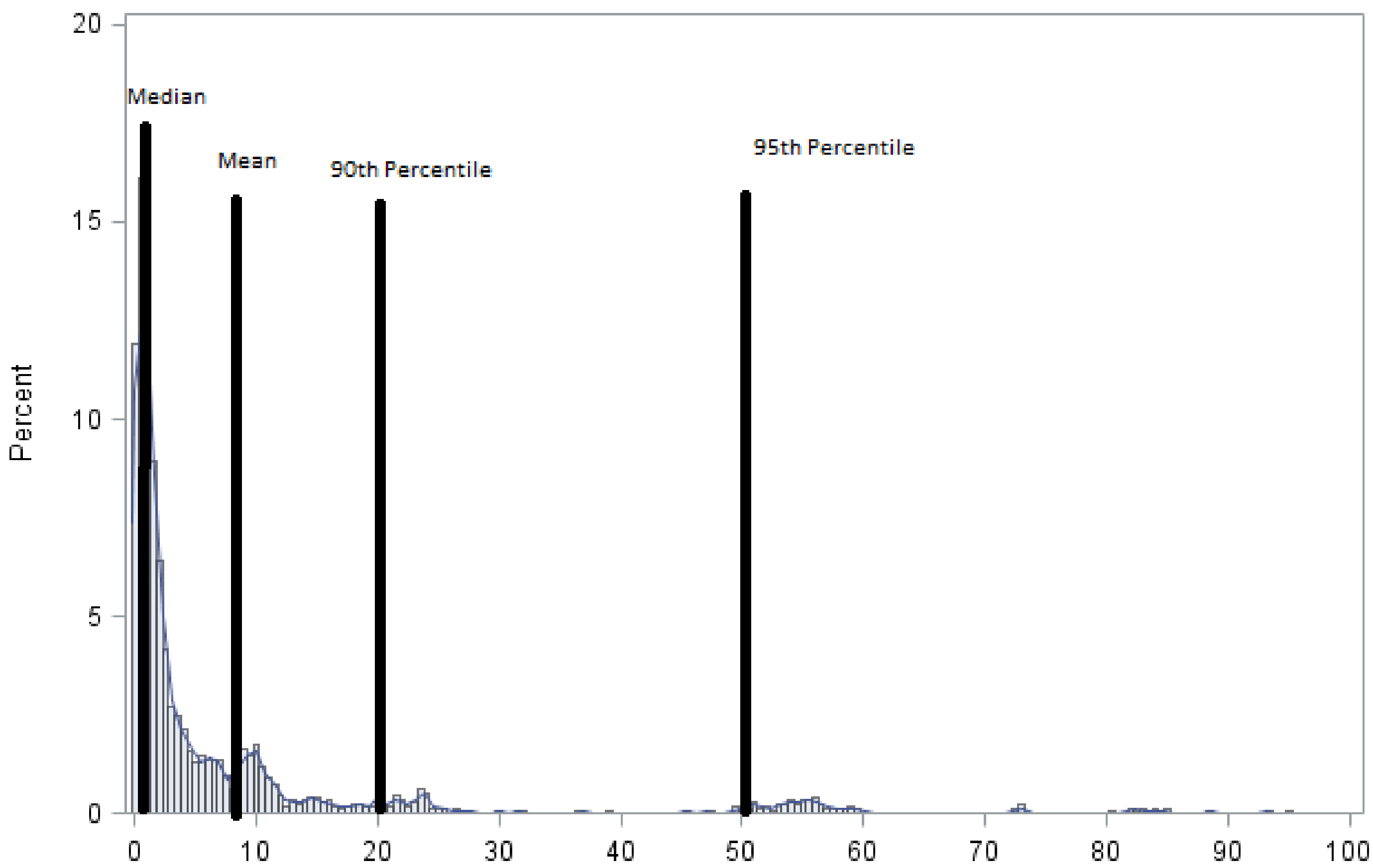
Distribution of differences between the highest low price and the lowest low price across issues of the same firm for each day after bankruptcy. Bin size for histogram is 0.5. Percent of observations in a bin are on the Y-axis. Sample is restricted to 30 days after bankruptcy. The solid line is a kernel density function with bandwidth of 0.1.

Figure 17: Distribution of differences in volume weighted prices across issues for each firm day



Distribution of differences between the highest volume weighted price and the lowest volume weighted price across issues of the same firm for each day after bankruptcy. Bin size for histogram is 0.5. Percent of observations in a bin are on the Y-axis. Sample is restricted to 30 days after bankruptcy. The solid line is a kernel density function with bandwidth of 0.1.

Figure 18: Distribution of differences in hourly prices across issues for each firm day



Distribution of differences between the highest hourly price and the lowest hourly price across issues of the same firm for each day after bankruptcy. Bin size for histogram is 0.5. Percent of observations in a bin are on the Y-axis. Sample is restricted to 30 days after bankruptcy. The solid line is a kernel density function with bandwidth of 0.1.

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